IS 11182-3-2 (1996): Guide for evaluation of insulation systems of electrical equipments, Part 3: Electrical endurance test procedures, Section 2: evaluation procedure based on extreme value distribution [ETD 2: Solid Electrical Insulating Materials and Insulation Systems]

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भारतीय मानक

(Reaffirmed 2001)

बिजली के उपकरणों के विद्युतरोधन पद्धति के मूल्यांकन हेतु मार्गदर्शन

भाग 3 वैद्युत सहन परीक्षण विधियाँ

अनुभाग 2 चरममान वितरण पर आधारित मूल्यांकन प्रक्रियाएँ

Indian Standard

GUIDE FOR THE EVALUATION OF INSULATION SYSTEMS OF ELECTRICAL EQUIPMENT

PART 3 ELECTRICAL ENDURANCE TEST PROCEDURES

Section 2 Evaluation Procedures Based on Extreme-Value Distributions

ICS 20.080

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Electrical Insulation Systems Sectional Committee, ETD 4

FOREWORD

This Indian Standard (Part 3/Sec 2) was adopted by the Bureau of Indian Standards, after the draft finalized by the Electrical Insulation Systems Sectional Committee had been approved by the Electrotechnical Division Council.

This standard is one in the series of standard dealing with guidelines for the evaluation of insulation systems of electrical equipment. These guidelines include method of identification and general principles of functional evaluation of insulation systems together with test procedures to evaluate the behaviour of systems under different factors of influence.

The purpose of this standard is to guide the development of system test procedures and suggest points to be considered by the equipment technical committees in the preparation of specific instructions for the evaluation of electrical endurance of insulation systems for electrical equipment.

This standard suggests techniques that may be used for data whose distribution does not correspond well with a normal (Gaussian) distribution, but may correspond to an extreme-value distribution.

The other parts of the standard are as follows:

IS 11182 Guide for the evaluation of electrical insulation system of electrical equipment:

Part 1	Identification, evaluation and ageing mechanism
Part 2	Thermal endurance test procedures
Part 3/ Sec 1	Electrical endurance test procedures, Section 1 General considerations and evaluation procedures based on normal distribution
Part 5	Mechanical endurance functional tests
Part 6	Performance evaluation based on service experience and functional tests
Part 7/ Sec 1	Multi factor functional testing, Section 1 Test procedures

In the preparation of this standard, assistance has been derived fron IEC Publication 727-2 (1993) 'Evaluation of electrical endurance of electrical insulation system: Part 2 Evaluation procedures based on extreme-value distribution', issued by the International Electrotechnical Commission (IEC).

For the purpose of deciding whether a particular requirement of this standard is complied with, the final value, observed or calculated, expressing the result of a test or analysis, shall be rounded off in accordance with IS 2 : 1960 'Rules for rounding off numerical values (*revised*)'. The number of significant places retained in the rounded off value should be the same as that of the specified value in this standard.

Indian Standard

GUIDE FOR THE EVALUATION OF INSULATION SYSTEMS OF ELECTRICAL EQUIPMENT

PART 3 ELECTRICAL ENDURANCE TEST PROCEDURES

Section 2 Evaluation Procedures Based on Extreme-Value Distributions

1 SCOPE

1.1 This standard describes statistical procedures to analyze data on time-to-breakdown at constant voltage stress (or breakdown voltages under long-term increasing-voltage stress) of groups of individual specimens of electrical insulation systems, or models representing insulating systems. Numerical examples are also included.

1.2 This standard assumes that the electrical factors of influence is the dominating ageing factor. If it is known or understood that more than one factor of influence is significant, reference should be made to IS 11182 (Part 7/ Sec 1) : 1986 'Guide for evaluation of insulation systems of electrical equipment: Part 7 Multi factor functional testing, Section 1 Test procedures'.

1.3 This standard does not apply to data derived from short-time electrical breakdown tests except those used as diagnostic factors from other long-term factors of influence. When used in this way for diagnosis of factors of influence other than electrical, reference should be made to other appropriate Indian Standards given in **2** of this standard.

2 REFERENCES

The following Indian Standards are the necessary adjuncts to this standard :

IS No.	*Title*
2071 (Part 1) : 1993	High voltage test techniques: Part 1 General definitions and test requirements (*second revision*)
11182	Guide for evaluation of insulation systems of electrical equipment:
(Part 1) : 1984	Identification, evaluation and ageing mechanism
(Part 2) : 1984	Thermal endurance test procedures
(Part 6) : 1986	Performance evaluation based on service experience and functional tests
(Part 7/ Sec 1) : 1986	Multi factor functional testing, Section 1 Test procedures

3 PROBABILITY DISTRIBUTIONS

The statistical analysis of a set of data presupposes that a probability distribution function has been chosen that is assumed to represent the variation of the data under the conditions of the test. In this guide two types of extreme-value distribution are described.

3.1 Extreme-Value Distributions

Extreme-value distributions have been found to represent a wide variety of data on systems that fail by a 'weakest-link' mechanism, and they are often employed to analyze time-to-breakdown and long-time breakdown-voltage data in insulation studies.

The extreme-value distributions are fundamentally different from the normal (Gaussian) distribution. This latter distribution best represents 'average' phenomena. Techniques commonly used for estimating normal distribution quantities are not generally applicable to the extreme-value distributions. In particular, the methods to calculate the mean, standard deviation, confidence intervals and hypothesis quantities for the normal distribution should not be applied to extreme-value distributions.

Two types of extreme-value distributions are the Weibull and the Gumbel distributions.

3.1.1 *Weibull Distribution*

The Weibull distribution is appropriate when the rate of failure varies with time. It is most often used to represent either time-to-failure results from a long-time constant voltage stress test, or breakdown voltage results form a long-time progressive voltage stress test, on solid insulations.

The three-parameter Weibull distribution has the

following equation:

$$F(x) = 1 - \exp\left[-\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right], x \geq \gamma \qquad ......(1)$$

where

α = scale parameter and is positive;

β = shape parameter and is positive;

γ = location parameter;

x = random variable, usually the time to breakdown or the breakdown voltage; and

$F(x)$ = probability of failure at time (or voltage) $\leq x$.

The probability of failure $F(x)$ is zero at $x < \gamma$. The probability of failure rises continuously as x increases. As the time or voltage increases to infinity, the probability of failure approaches certainly, that is $F(x=\infty)=1$.

The scale parameter (α) represents the time (or voltage) required for ($1- e^{-1}$) or 63.2 percent of the tested specimens to fail. It is analogous to μ, the mean of the normal distribution*. The unit of α is the same as that of x, that is, hours or volts.

The shape parameter (β) is a measure of dispersion of the log failure times or log voltages. The larger β is, the smaller is the range of log times or log breakdown voltages. The shape parameter, which is dimensionless, is analogous to $1/\sigma$, where σ is the standard deviation of the normal distribution*.

When the shape parameter (β) is less than 1, the failure rate decreases with time; when greater than 1, the failure rate increases with time.

When the shape parameter (β) is equal to 1, the Weibull distribution is equivalent to the exponential distribution and the failure rate is independent of time.

The location parameter (γ) represents a value below which the probability of occurrence of x is zero. It represents a threshold value, below which a certain physical phenomena (failure) does not occur. The unit of γ is the same as that of x.

The estimation of three Weibull parameters requires the solution of non-linear equations, and is not possible by a two-dimensional graphical solution.

The two-parameter Weibull distribution is a particular case of the three-parameter distribution, when the location parameter (γ) is zero. This latter implies that the phenomenon being studied has a threshold value equal to zero.

One a two-dimensional graphical representation, the divergence of the true graph from a straight line will increase as the difference between the true value and the assumed value of the location parameter (γ) increases.

The two-parameter Weibull distribution has the following equation:

$$F(x) = 1 - \exp\left[-\left(\frac{x}{\alpha}\right)^{\beta}\right], x \geq 0 \qquad ......(2)$$

3.1.2 *Gumbel Distribution*

The Gumbel distribution is most often used to represent the breakdown voltages of liquid insulation and of compressed gas insulations with slightly non-uniform fields. The cumulative Gumbel distribution function for the population fraction below y is:

$$G(y) = 1 - \exp\left[-\exp\left(\frac{y-u}{b}\right)\right], -\infty \leq y \leq \infty \quad ....(3)$$

where

u = location parameter and may have any value;

b = scale parameter and is positive;

y = random variable, usually the breakdown voltage; and

$G(y)$ = probability of failure at voltage (or time) less than or equal to y.

The Gumbel distribution is unsymmetrical and has a physically impossible finite probability of breakdown for $y < 0$, but if $u >> b$, this probability will be negligibly small. This distribution is also called the smallest extreme-value (that is, weakest-link) distribution. The unit of u and b is the same as that of y.

The Gumbel distribution is closely related to the Weibull distribution. That is, if x has a Weibull distribution, then $y = \text{In}\,(x)$ has a Gumbel distribution where:

$$u = \text{In}\,\alpha \qquad ......(4)$$

$$b = \frac{1}{\beta} \qquad ......(5)$$

Estimation techniques employed for one distribution (Gumbel or Weibull) apply to the other if the transformation equations (4) and (5) are utilized.

4 TREATMENT OF TEST DATA

4.1 Censored Data

Censored data occur when n specimens are started on test together and the times to breakdown of only r ($< n$) are observed. Censoring is encountered mainly with constant voltage stress tests, where the data are

*Note that a mean and a standard deviation can be defined for the Weibull distribution. These quantities however, are seldom used.

analyzed or the test is terminated before all the specimens fail. Censoring can also occur with progressive-stress tests where flashovers or spurious breakdowns occur on specimens which survive to high stresses. Since censoring can occur by plan or by accident in many insulation tests, it should be taken into account in the data analysis.

There are at least two types of censoring:

Type I : Occurs when the test is terminated (or the data are analysed) after a certain period of time (or given maximum test voltage). Suppose x_s is the time the test is stopped and x_r is the time of the rth and last observed failure ($x_s > x_r$), then $(n-r)$ unfailed specimens survived beyond time x_s.

Type II : Occurs when the test is terminated immediately after the rth failure, that is, $x_s = x_r$.

There are also other kinds of censoring, such as progressive and multiple censoring.

These types result, for example, when failed specimens are disqualified because of specimen failure by spurious mechanisms. Analytical treament of such data is more difficult.

4.2 Selection of a Probability Distribution

Solid insulation test data are often represented by the two-parameter Weibull distribution whereas the Gumbel (smallest extreme-value) distribution is often employed for liquids. However, the validity of the assumed distribution should be tested since it is possible that another distribution will yield a better fit, unless prior experience or theory indicates that a particular distribution is valid.

Testing the validity of the assumed distribution to best represent the test data can most easily be accomplished by the use of probability graph paper.

This paper has one axis in the form of a non-linear cumulative probability scale, which is the same for both the Weibull and the Gumbel distributions. The other axis, on which are plotted the failure times or breakdown voltage, is lograithmic for the Weibull distribution and linear for the Gumbel distribution. The axis are scaled so that data from the respective distributions will follow a straight line on the corresponding graph paper.

Other methods to test the validity of assumed distributions include statistical fitness tests, or comparison by the maximum likelihood method.

4.2.1 *Weibull Probability Graph Paper*

A sample of Weibull probability paper is shown in Fig. 1A. To use this paper, order the failure times or voltages from smallest to largest. The cumulative probability of the ith smallest value (x_i) is approximated by the formula :

$$F(x_i) = \frac{i}{n+1} \qquad \text{......(6)}$$

where n is the total number of test specimens. The Weibull example data in Table 1 are plotted in Fig. 1A. Data from unfailed specimens should not be plotted, although they should be included in n. Specimens that have failed by mechanisms that are clearly spurious and invalid, should be disqualified, and not counted in n.

If the plotted data follow a straight line, then it may be reasonable to assume that the results are adequately represented by the Weibull distribution. Some random deviations from a straight line would normally be expected. If, however, there is a consistent departure from a straight line (say, curvature), then another distribution may fit the data better. Figure 2 shows Weibull probability plots of data from other distributions.

4.2.2 *Gumbel Probability Graph Paper*

A sample of Gumbel probability paper is shown in Fig. 3A. As with the Weibull paper, the failure times or voltages are ordered from smallest to largest, and the cumulative probability for the ith smallest value (y_i) is approximated by the formula:

$$G(y_i) = \frac{i}{n+1} \qquad \text{......(7)}$$

where n is the totoal number of test specimens.

If the data plot as a straight line on the Gumbel paper, then the Gumbel distribution adequately represents the failure data. Examples of data from other distributions are plotted on Gumbel paper in Fig. 4.

4.2.3 *Graph Paper Availability*

The graph papers described in **4.2.1** and **4.2.2** are generally commercially available.

However, if double natural-logarithmic transformations are made, the Weibull function becomes linear with respect to $\ln x$, and the data may be plotted on standard arithmetic paper. Appropriate data will form straight lines.

4.3 Estimation of Distribution Parameters

The distribution parameters may be estimated graphically or by calculation. The calculated estimates are more objective than the graphical estimates and are preferred.

4.3.1 *Graphical Estimation of Parameters*

The probability graph papers described in **4.2** can be used to obtain approximate estimates of the parameters, from the slope and intercept of the straight line fitted to the data points 'by eye'.

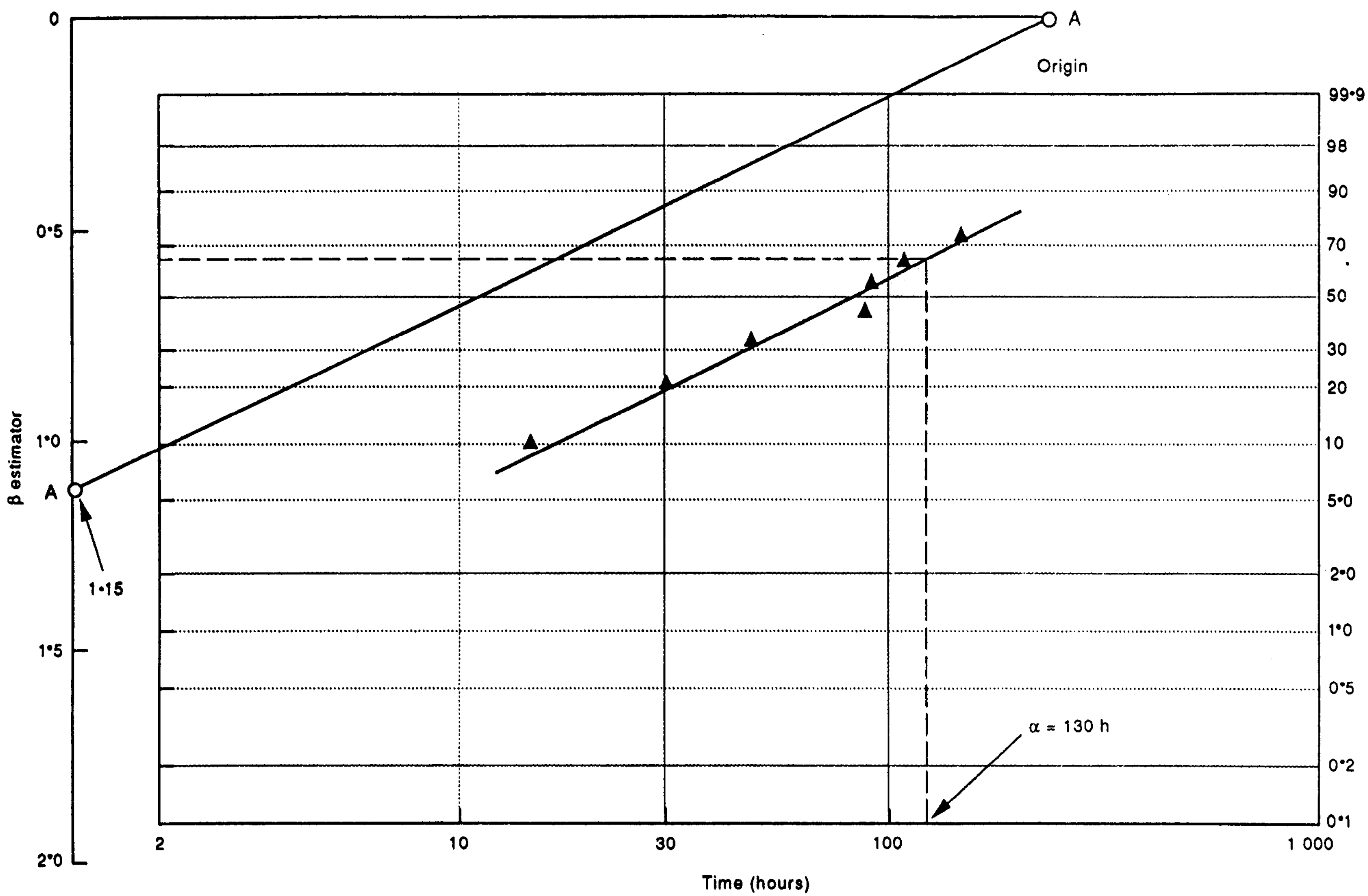

FIG. 1A WEIBULL PLOT OF FAILURE DATA WITH LINE FIT 'BY EYE'

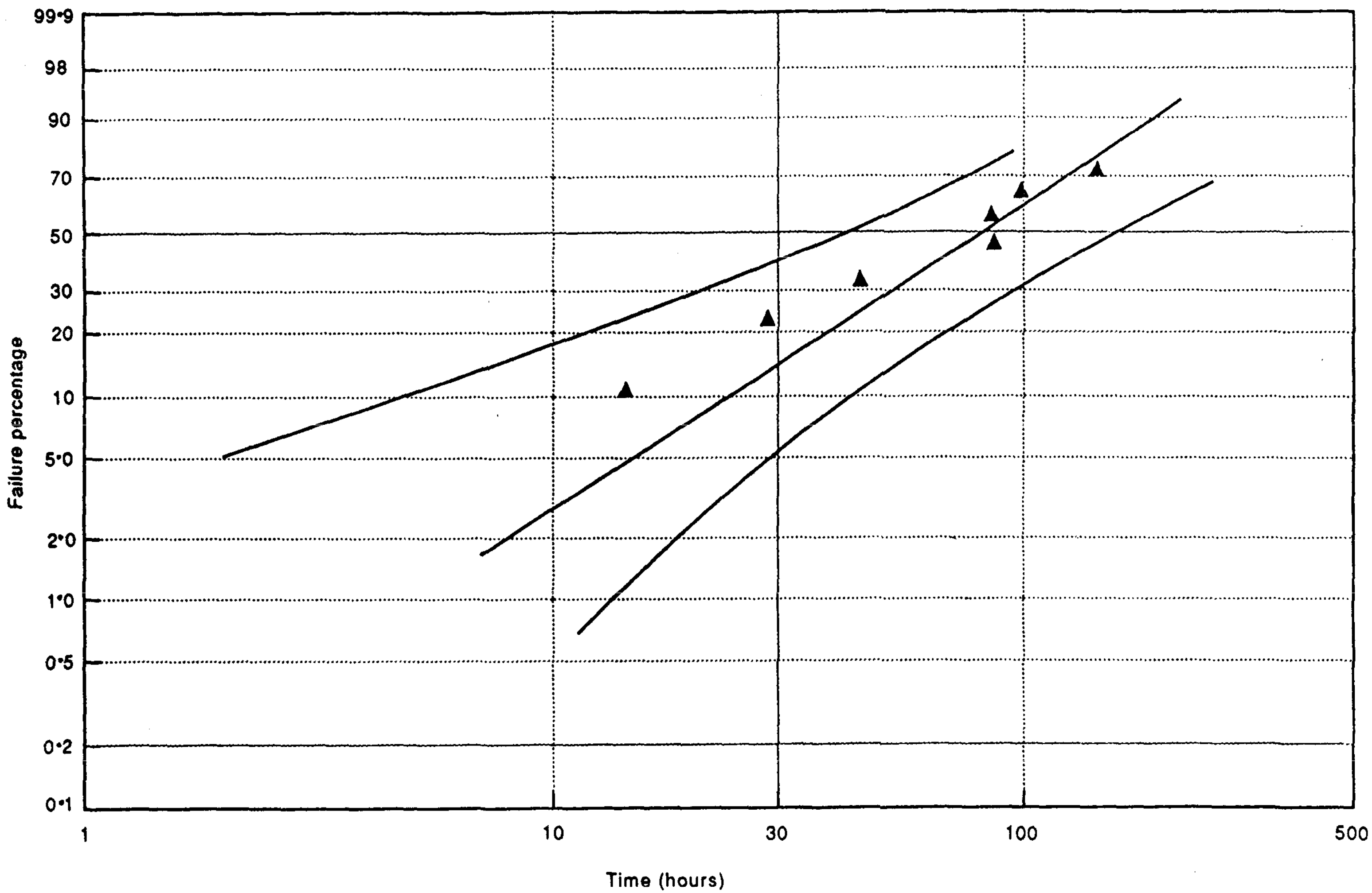

FIG. 1B WEIBULL PLOT OF 90 PERCENT CONFIDENCE BOUNDS FOR PERCENTILES AND MAXIMUM LIKELIHOOD FITTED LINE

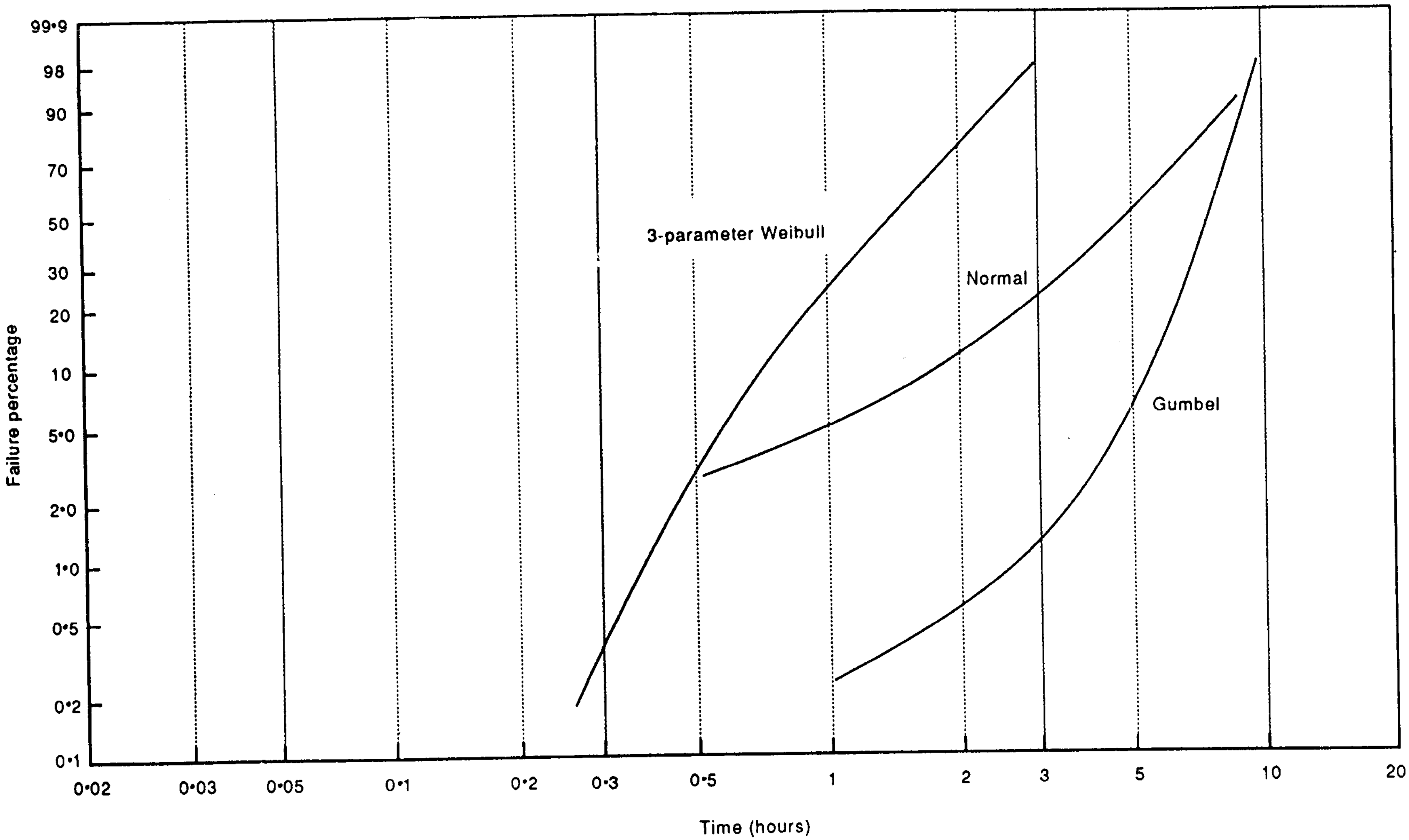

FIG. 2 PLOT OF OTHER DISTRIBUTIONS ON 2-PARAMETER WEIBULL PAPER

Confidence intervals for parameters cannot be estimated graphically.

4.3.1.1 *Graphical estimates for the Weibull distribution*

Plot the test data on Weibull probability paper, as described in **4.2.1**. Fit a striaght line 'by eye' to the data points. The estimate for the scale parameter (α), denoted by ($\hat{\alpha}$) is the time (or voltage) corresponding to $F(x) = 63.2$ percent. An estimate for the shape parameters (β) denoted by ($\hat{\beta}$), is calculated from:

$$\hat{\beta} = \frac{\ln(\ln L_1) - \ln(\ln L_2)}{\ln\left(\frac{x_1}{x_2}\right)} \qquad \text{......(8)}$$

where

$$L_1 = \frac{1}{1 - F(x_1)} \qquad \text{......(9)}$$

$$L_2 = \frac{1}{1 - F(x_2)} \qquad \text{......(10)}$$

ln ( ) represents the natural logarithm and $[x_1, F(x_1)]$, $[x_2, F(x_2)]$ correspond to two points on the fitted line. Most commercial Weibull probability papers contain a special scale which permits the rapid estimation of β.

For the data from Table 1 plotted in Fig. 1A, $\hat{\alpha} = 130$ h. Using the two points (160, 0.7) and (30, 0.16) obtained from the fitted line, $\hat{\beta} = 1.15$ using equation (8). The line labelled A-A, drawn through a point labelled 'origin' in Fig. 1A, is parallel to the fitted line and gives an estimate of 1.15 for β.

4.3.1.2 *Graphical estimates for the Gumbel distribution*

Plot the test data on Gumbel probability paper, as described in **4.2.2**. Fit a straight line 'by eye' to the data points. The estimate of the location parameter (u), denoted by ($\hat{u}$), is the voltage corresponding to $G(y) = 63.2$ percent. An estimate of the scale parameter (b), denoted by ($\hat{b}$), is the difference between the 63 percent and 31 percent points.

For the data from Table 2 plotted in Fig. 3A, $\hat{u} = 5.84$ kV. Using the two percentage points, from the fitted line, $\hat{b} = 5.84 - 5.43 = 0.41$ kV.

4.3.2 *Calculated Estimation of Parameters*

The most widely used parameter estimates are the maximum likelihood estimates, which are valid for both Type I and Type II censored data. They are asymptotically unbiased and their variances are not larger than the variances of any other estimates, for example those derived from the least-squares method. However, for large sample sizes (for example $n > 50$) of uncensored data, transformed as described in **4.2.3**, the errors inherent in linear regression methods, such as the least-squares method, are not usually apparent.

4.3.2.1 *Calculated estimates for the Weibull distribution*

For the Weibull distribution, the maximum likelihood estimates of $\hat{\alpha}$ and $\hat{\beta}$ require the iterative solutions of:

$$f(\beta) = \frac{A_2}{A_1} - \frac{1}{\beta} - C = 0 \text{ and} \qquad \text{.....(11)}$$

and

$$\hat{\alpha} = \left(\frac{A_1}{r}\right)^{\frac{1}{\hat{\beta}}} \qquad \text{......(12)}$$

where

$$A_k = \sum_{i=1}^{r} x_i^{\hat{\beta}} [\ln x_i]^{(k-1)} + (n-r)\, x_s^{\hat{\beta}} [\ln x_s]^{(k-1)} \qquad \text{...... (13)}$$

for $k = 1, 2, 3$ (A_3 is required for the iterative solution).

$$C = \left(\frac{1}{r}\right) \sum_{i=1}^{r} \ln x_i \qquad \text{......(14)}$$

where

- x_s = running time or highest test voltage of the experiment,
- n = total number of specimens tested, and
- r = number of specimens that failed.

For Type II censoring, $x_s = x_r$.

A short BASIC programme solving these equations on a personal computer is shown in Annex A. Most computer programs require an initial guess for β. This is most easily obtained from a Weibull probability plot. In lieu of probability plot, an initial β of 10 may be applicable for progressive-stress tests. For constant-stress tests, an initial β of 2 may be applicable.

The maximum likelihood estimates for the data in Table 1 are $\hat{\alpha} = 115$ h and $\hat{\beta} = 1.5$. The line on Weibull probability paper which fits these data is shown in Fig. 1B. The line is plotted by substituting two values of x, along with $\hat{\alpha}$ and $\hat{\beta}$ into equation (2) and calculating the corresponding values of $F(x)$.

4.3.2.2 *Calculated estimates for the Gumbel distribution*

A separate set of equations to yield the maximum likelihood estimates could be generated for the Gumble distribution . However, it is simpler to employ the

transformations in equations (4) and (5) with a computer program that fits the Weibull distribution. In particular, the Gumbel test data (y_i) are first transformed into Weibull data with:

$$x_i = \exp(y_i) \qquad \text{......(15)}$$

A first estimate for $\beta = \frac{1}{b}$ can be obtained from a Gumbel probability plot. Alternatively, assume an initial b of 0.1 (that is, $\beta = 10$). The programme output of α and β are then:

$$\hat{u} = \ln \hat{\alpha} \qquad \text{......(16)}$$

$$\hat{b} = \frac{1}{\hat{\beta}} \qquad \text{......(17)}$$

For the Gumbel data in Table 2, $\hat{u}$ = 5.73 kV and $\hat{b}$ = 0.26 kV. With two values of y and the parameter estimates, corresponding values of $G(y)$ can be calculated. These two points will define the straight line on Gumbel paper (Fig. 3B.)

4.4 Confidence Intervals for Parameters

If the same experiment involving the testing of many specimens is performed a number of times, the values of the parameter estimates ($\hat{\alpha}$ $\hat{\beta}$ *or* $\hat{a}$ $\hat{b}$) from each experiment differ. This variation in estimates results from the statistical nature of insulation breakdown. Therefore, any parameter estimate differs from the 'true' parameter value of the total population which could be obtained from an experiment involving an infinitely large number of specimens. Hence, it is common to give with each parameter estimate a 'confidence interval', which encloses the true parameter value with high probability. The confidence interval objectively quantifies the uncertainty in the estimate of the parameter. In general, the more specimens tested, the narrower will be the confidence interval.

If an experiment is poorly performed, for instance if the applied voltage is not held constant in a constant stress test, the confidence intervals are inaccurate. Confidence intervals are valid only for *identically* tested specimens.

There are various confidence intervals for Weibull and Gumbel parameters and percentiles. The recommended intervals employ maximum likelihood parameter estimates. This method, which is valid for all sample sizes and Type II censoring, requires an extensive computer programmes which is not generally available. Many available computer programmes give parameter estimates and approximate confidence intervals. However, their validity should be checked by comparison to reputable main-frame programmes.

Many tables similar to Student's t table have been calculated for the extreme-value distributions. For those without access to large computers, approximate confidence intervals based on these tables can be determined.

4.4.1 *Approximate Confidence Intervals for Weibull Parameters*

There are various methods and tables for calculating approximate confidence intervals for α and β. The most complete tables are based on best linear invariant estimates for the parameters, rather than the maximum likelihood estimates.

The confidence intervals tables for α and β, which cover all possible censoring fractions are very extensive. For simplicity these tables are represented as curves in Fig. 5 and 6. These curves are approximate, valid only for Type II censoring, and are for experiments with up to 25 specimens tested. Type I censored data can be analyzed with some bias in the estimates by setting $x_r = x_*$. Figure 5 and 6 give 90 percent confidence intervals only. For more accurate intervals, other sample sizes, etc., computer-based methods will be necessary.

Figure 5 is used to compute the 90 percent confidence intervals for the shape paramenter β:

$$\beta_l = W_l\, \hat{\beta} \qquad \text{......(18)}$$

$$\beta_u = W_u\, \hat{\beta} \qquad \text{......(19)}$$

where β_l and β_u are the lower and upper bounds, respectively, for the interval. As seen in Fig. 5, W_l and W_u are mainly functions of r, the number of failures. For the Weibull data in Table 1, $W_l = 0.42$ and $W_u = 1.46$ and, since β 1.5 (*see* **4.3.2.1**), the 90 percent confidence limits for β are $\beta_l = 0.42 \times 1.5 = 0.63$ and $\beta_u = 1.46 \times 1.5 = 2.2$.

Fig. 6 is used to calculate the 90 percent confidence intervals for the scale parameter (α):

$$\alpha_l = \hat{\alpha} \exp\left[\frac{Z_l}{\hat{\beta}}\right] \qquad \text{......(20)}$$

$$\alpha_u = \hat{\alpha} \exp\left[\frac{Z_u}{\hat{\beta}}\right] \qquad \text{......(21)}$$

where α_l and α_u refer to the lower and upper confidence bounds, respectively. The factor Z_l is primarily a function of n, the number of specimens put on test. Z_u, however, is a function of both r, the number of specimens which actually failed, and n. For the Weibull data in Table 1, $Z_l = 0.75$ and $Z_u = 1.0$. Therefore, the 90 percent confidence limits for α are $\alpha_l = 69$ h and $\alpha_u = 220$ h.

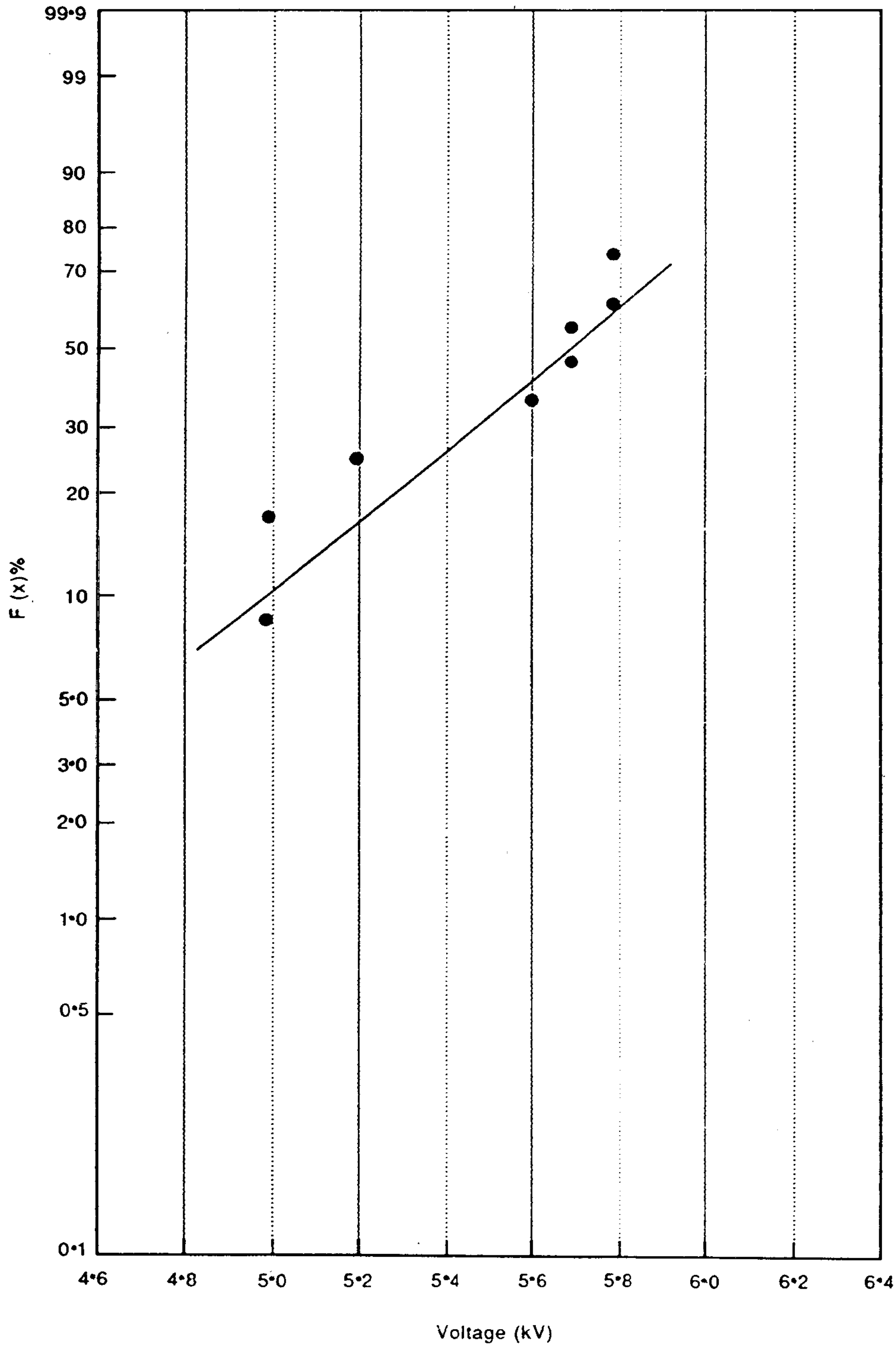

FIG. 3A GUMBEL PROBABILITY PLOT OF DATA IN TABLE 2 (THE LINE IS FITTED BY EYE)

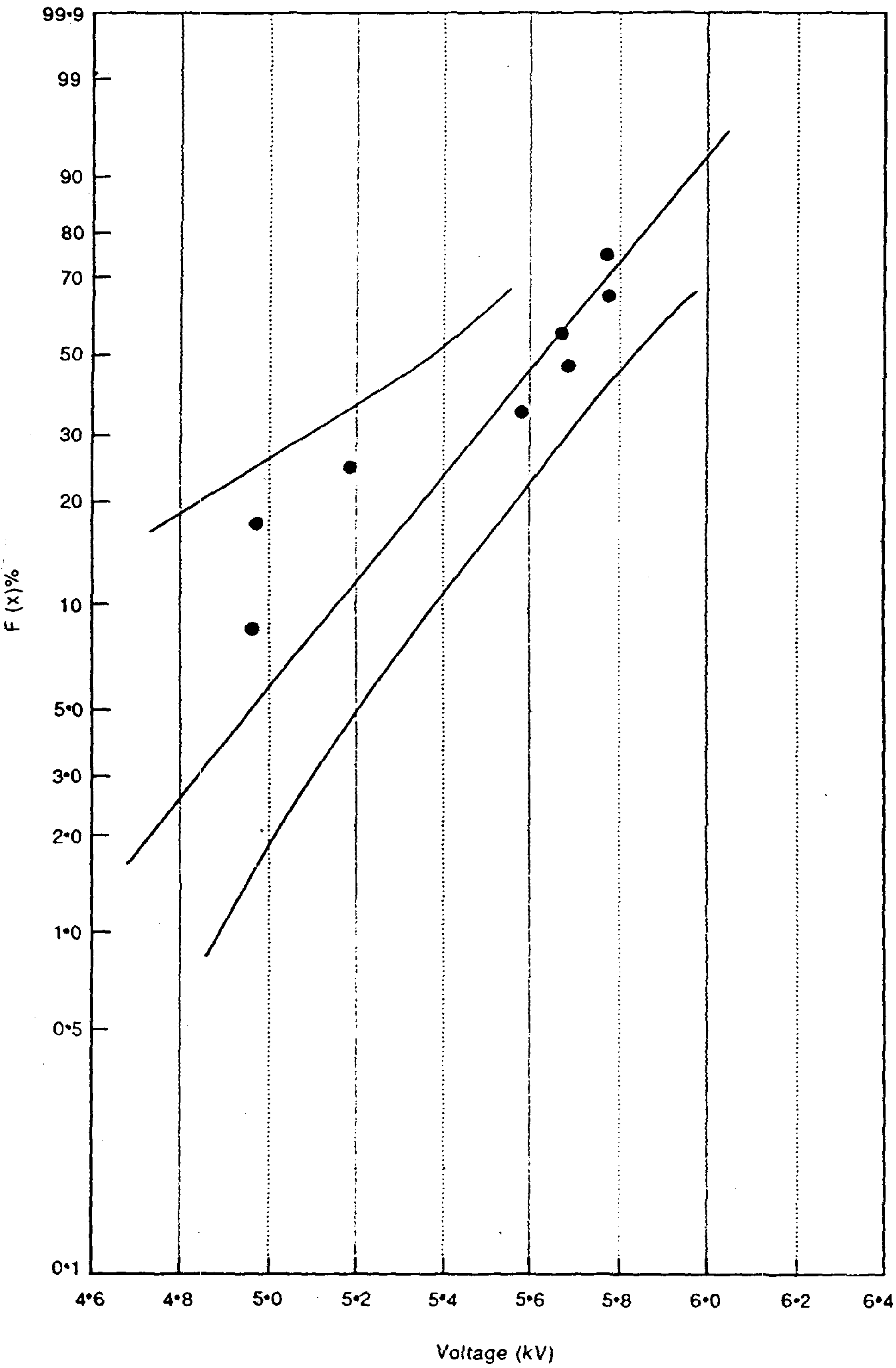

FIG. 3B 90 PERCENT CONFIDENCE BOUNDS ON MAXIMUM LIKELIHOOD FITTED LINE

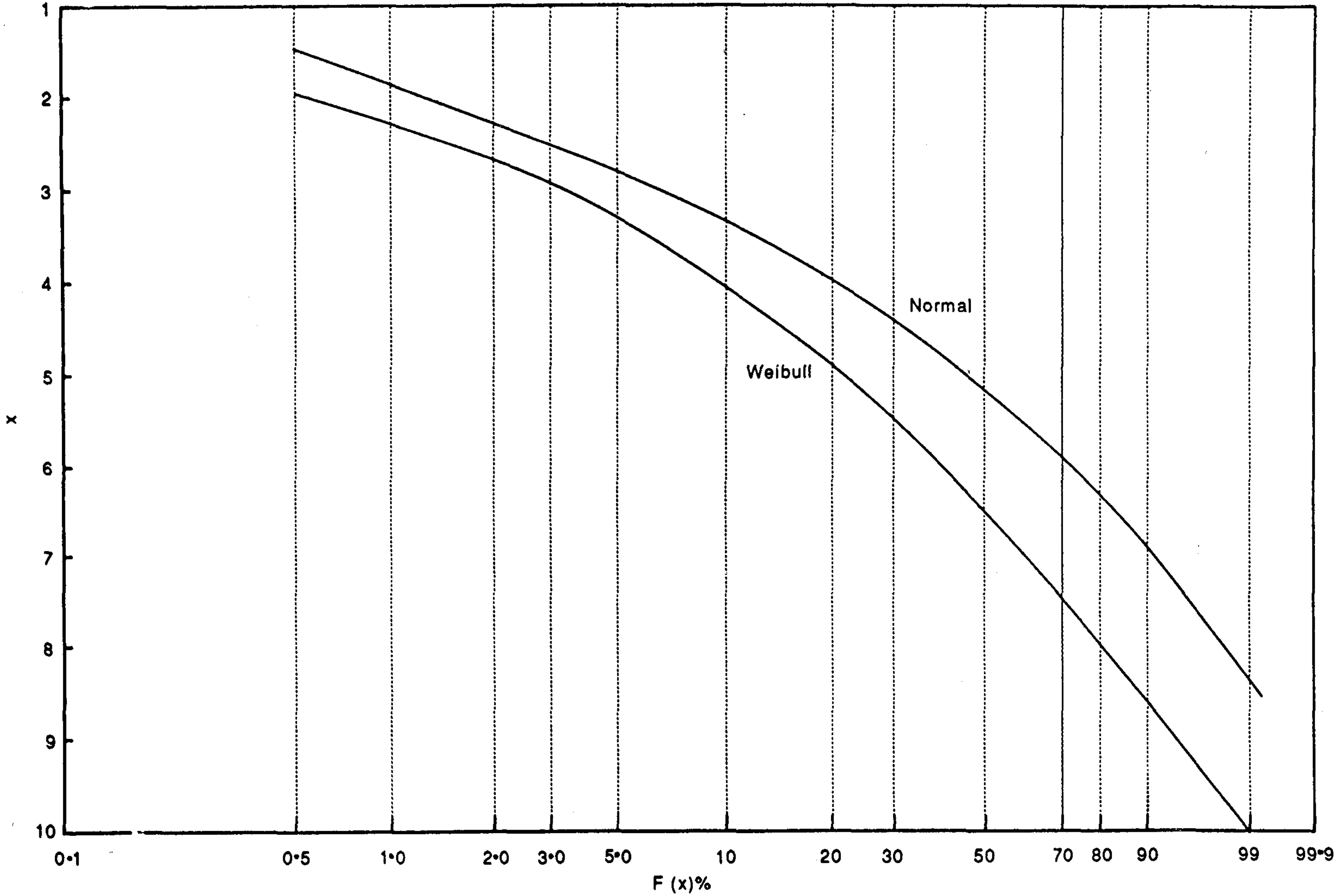

FIG. 4 PLOTS OF OTHER DISTRIBUTIONS ON GUMBEL PROBABILITY PAPER

4.4.2 *Approximate Confidence Intervals for Gumbel Parameters*

The same curves used for the Weibull parameter intervals can be used for the Gumbel parameters. As before, the curves in Fig. 5 and Fig. 6 yield approximate 90 percent confidence intervals for Type II censored data.

The approximate 90 percent confidence intervals for b has lower and upper limits:

$$b_1 = \frac{\hat{b}}{W_u} \qquad \text{......(22)}$$

$$b_1 = \frac{\hat{b}}{W_1} \qquad \text{......(23)}$$

Note that the W_u factor from Fig. 6 is for the lower bound and W_1 is for the upper bound. For the Gumbel data in Table 2, W_u= 1.44 and W_1 = 0.45; thus b_1= 0.18 kV and b_u= 0.58 kV are the confidence limits for b.

The approximate 90 percent confidence intervals for u has lower and upper limits:

$$u_1 = \hat{u} - \hat{b}\, Z_1 \qquad \text{......(24)}$$

$$u_1 = \hat{u} + \hat{b}\, Z_u \qquad \text{......(25)}$$

The Z factors are obtained from Fig. 6A and 6B. For the Gumbel data in Table 2, Z_1= 0.7 and Z_u= 1.12. Thus the 90 percent confidence intervals for u has limits u_1= 5.57 kV and u_u=6.04 kV.

4.5 Percentiles

In addition to estimating the parameters of a distribution, in many cases it is of interest to calculate the time-to-breakdown or the breakdown voltage at low probabilities of failure. The values of x and y at a particular probability of failure are referred to as percentiles if the probability is expressed in per cent.

4.5.1 *Confidence Intervals for Percentiles*

Many available computer programmes give estimates and confidence intervals (sometimes known as tolerance bounds) for percentiles,but their validity should be checked by comparison with reputable main-frame programmes. Approximate methods are available to calculate confidence intervals for percentiles, with the same theoretical basis as the intervals in **4.4**, for those without access to a valid computer programme. Tables upon which the curves in Fig. 7 are based are available only for the first, fifth and tenth percentiles, but other tables are available in the literature.

4.5.1.1 *Confidence intervals for Weibull percentiles*

The maximum likelihood estimate of the pth quantile, or (100p)th percentile ($\hat{x}_p$), for the Weibull distribution is:

$$\hat{x}_p = \hat{\alpha}\,[\,-\ln(1-p)]^{\frac{1}{\hat{\beta}}} \qquad \text{......(26)}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are thg maximum-liklihood parameter estimates. The confidence interval for x_p is:

$$x_1(p) = \hat{\alpha}\exp\left[\frac{V_1}{\hat{\beta}}\right] \qquad \text{......(27)}$$

$$x_u(p) = \hat{\alpha}\exp\left[\frac{V_u}{\hat{\beta}}\right] \qquad \text{......(28)}$$

where $x_1(p)$ and $x_u(p)$ refer to the lower and upper bound for the (100 p)th percentile, respectively. The V factors are obtained from Fig. 7A and 7B for the first, fifth and tenth percentiles (p = 0.01, 0.05 and 0.10 respectively). V_1 is primarily only a function of r, whereas V_u is primarily a function of n.

For the Weibull data in Table 1, for the first percentile, V_1= 10.4 and V_u= 3.1. Thus the 90 percent confidence limits are $x_1(0.01)$ = 0.11 h and x_u (0.01) = 14 h. The best estimate of the first percentile is $\hat{x}_p$ = 5.3 h.

The confidence limits for the percentiles, together with the confidence interval for α can be usefully displayed on Weibull probability paper. For the upper bound, plot the calculated upper limits (x values) corresponding to the first, fifth, tenth and 63.2 (α) percentiles on the graph paper. Join these four points with a smooth line. Similarly, draw a line for the lower confidence limits. As shown in Fig. 1B, these confidence limits will bound the 'best' line calculated from the maximum likelihood parameters. On repeated tests, the best lines should predominantly fall within the confidence bounds. The greater the number of samples tested, the narrower will be the gap between the upper and lower bounds.

4.5.1.2 *Confidence intervals for Gumbel percentiles*

The maximum likelihood estimate of the pth quantile, or (100p)th percentile ($\hat{y}_p$), for the Gumbel distribution is:

$$\hat{y}_p = \hat{u} + \hat{b}\,\ln\left[\ln\left(\frac{1}{1-p}\right)\right] \qquad \text{......(29)}$$

Where $\hat{u}$ and $\hat{b}$ are the maximum likelihood parameter estimates. The confidence interval for y_p is :

$$y_1(p) = \hat{u} - \hat{b}\, V_1 \qquad \text{......(30)}$$

$$y_u(p) = \hat{u} - \hat{b}\, V_u \qquad \text{......(31)}$$

where $y_1(p)$ and y_u(p) are the lower and upper limits for the (100 p)th percentile. The V_1 and V_u factors for the relevant percentile are obtained from Fig. 7A and 7B.

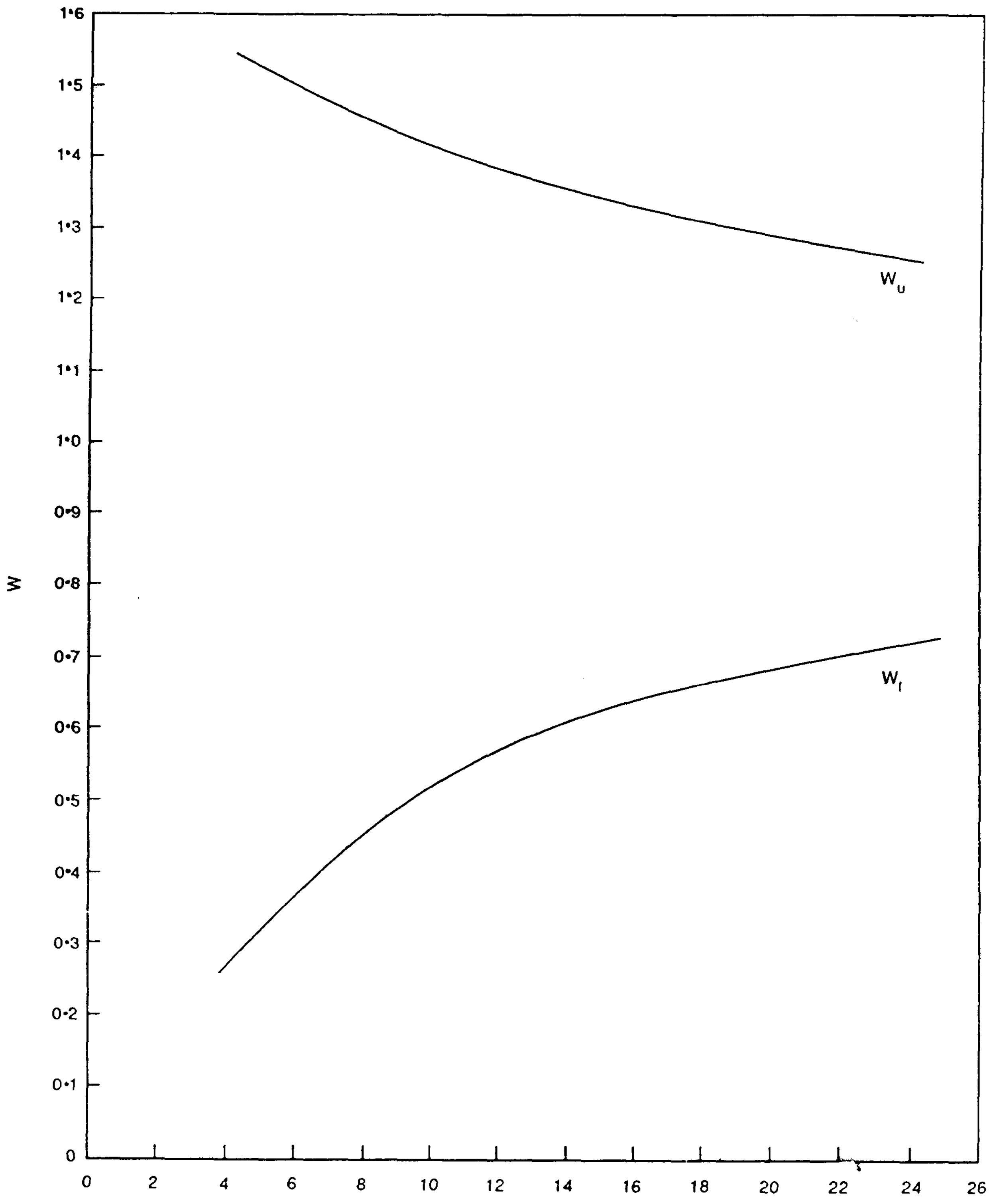

FIG. 5 *W* FACTORS FOR CALCULATING 90 PERCENT CONFIDENCE INTERVALS FOR $\hat{\beta}$ et $\hat{b}$

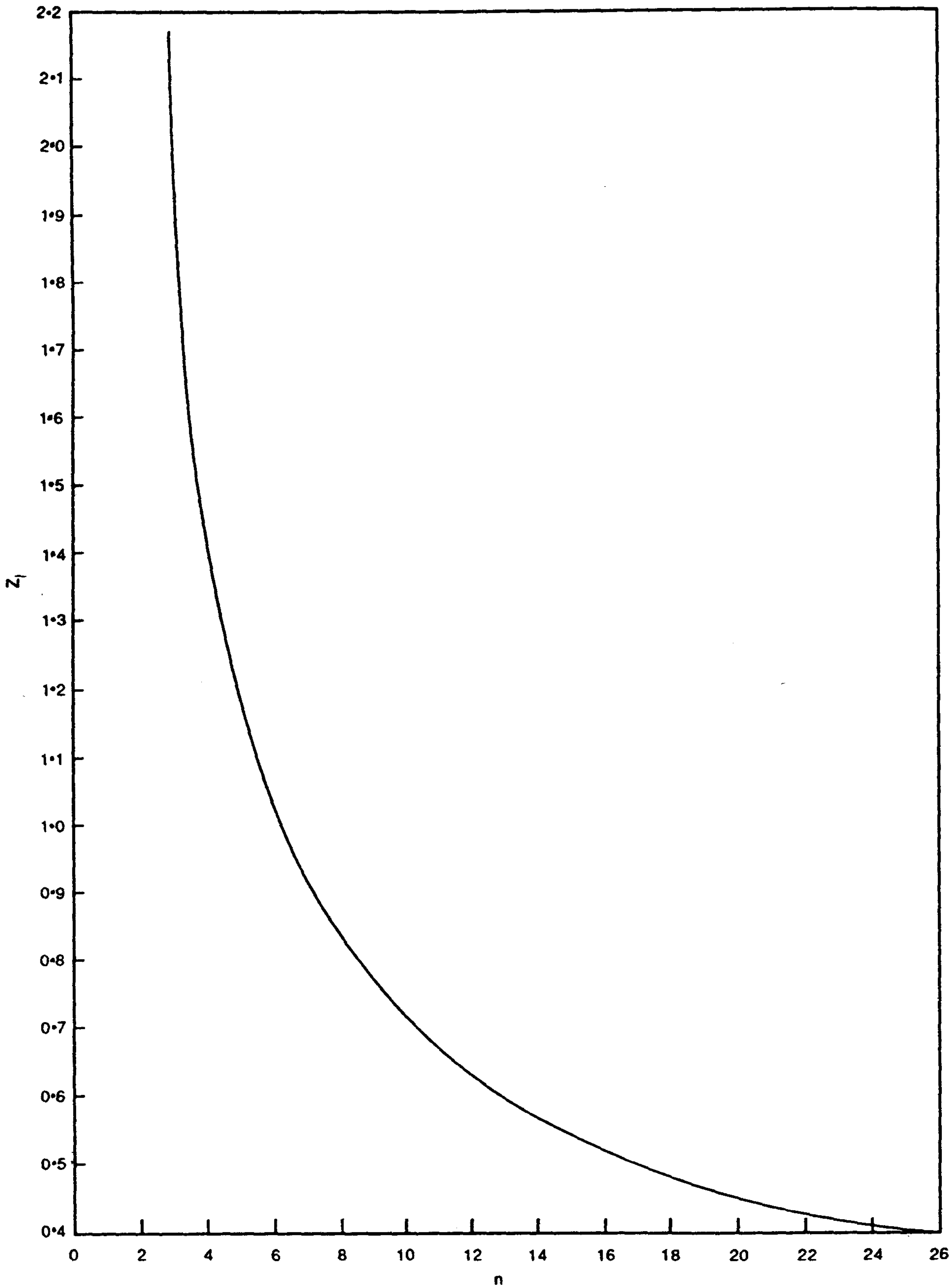

Fig. 6A Z_1 Factor to Calculate 90 Percent Confidence Interval for α_1 and u_1

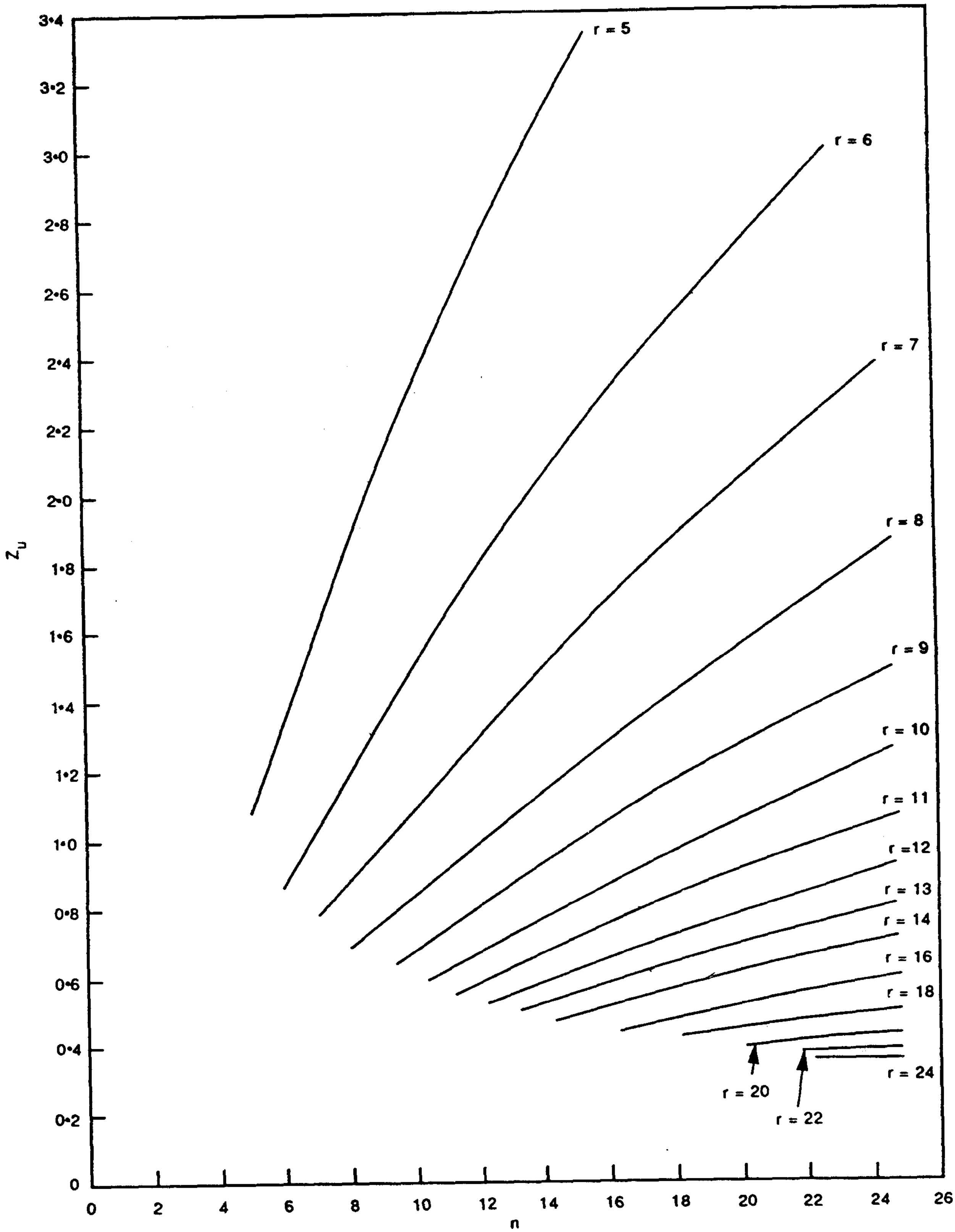

FIG. 6B Z_u FACTOR TO CALCULATE 90 PERCENT CONFIDENCE BOUNDS FOR α_u AND u_u

For the Gumbel data in Table 2, for the fifth percentile, $V_l = 6.4$ and $V_u = 2.0$, thus the 90 percent confidence limits are $y_l(0.05) = 4.1$ kV and $y_u(0.05) = 5.2$ kV. The maximum likelihood estimate of the fifth percentile is $\hat{y}_p = 4.95$ kV. The confidence bounds for the percentiles, together with the confidence bounds for b, can be plotted on Gumbel paper (Fig. 3B).

Table 1 Breakdown Data on Epoxy Specimens

(*Clauses* 4.3.1.1, 4.4.1 *and* 4.5.1.1)

Specimen No. i	$F(t_i)$ Percent	Breakdown Time t_i hours
1	10	15.3
2	20	30.3
3	30	48.5
4	40	89.4
5	50	90.4
6	60	105.7
7	70	144.9
8	80	–
9	90	–

Table 2 Breakdown Voltage of Oil

(*Clauses* 4.3.1.2, 4.4.2, 4.3.2.2 *and* 4.5.1.2)

Specimen No. i	$G(y_i)$ Percent	Breakdown Voltage y_i (kV)
1	9	5.0
2	18	5.0
3	27	5.2
4	36	5.6
5	45	5.7
6	54	5.7
7	64	5.8
8	73	5.8
9	82	–
10	91	–

5 COMPARISONS

A common situation involves testing two (or more) insulation systems to determine which of the two is a 'superior' insulation. Analysis of the results from such tests involves proving or disproving the hypothesis that there is a significant difference between the probability distributions of the data for the two systems. The 'hypothesis test' is usually performed on the distribution parameters or at a given percentile, for example 63 percent, 50 percent or 31 percent probabilities. For power systems insulation, it may be relevant to test for significant differences at low probabilities of failure, say 1 percent or 5 percent.

The easiest approach to compare the results of tests on two types of insulation is to plot the test data for each insulation on probability paper. However, this method can be misleading. This section outlines rigorous hypothesis test methods and presents an approximate simplified graphical procedure.

5.1 Rigorous Hypothesis Tests

Various methods are available to test the hypothesis that one set of test results is 'significantly' different from another. The following discussion is based on the Weibull distribution but, with the transformations in equations (4) and (5), it applies equally well to the Gumbel.

It is difficult to compare the distributions of two (or more) sets of data directly. Instead, the following specific hypotheses, among others, are possible.

$$H_\beta : \beta_1 = \beta_2 \quad \text{......(32)}$$

$$H_\alpha : \alpha_1 = \alpha_2 \quad \text{......(33)}$$

$$H_p : x_{1p} = x_{2p} \quad \text{......(34)}$$

where the subscript p refers to the pth percentile of the Weibull data, and the subscripts 1 and 2 to data sets No. 1 and No. 2. The tests of this hypotheses H_α and H_p often assume H_β to be true.

Rigorous means for proving or disproving the above hypothesis are usually based on 'likelihood ratio' methods or chi-square (χ^2) approximations. Some tables are available for calculating the significance levels, but these tables do not cover all sample sizes or censoring. Computer programmes are available which are based on the likelihood ratio principle. Specific use of these programmes and the interpretation of the results will be discussed in the programme's documentation. For those without access to appropriate computer programmes, a simplified 'graphical' approach is presented.

5.2 Simplified Method to Compare Percentiles

An approximate technique to determine if two data sets are different is to determine whether the confidence intervals at any percentile of the two distributions overlap, or not. If, for example, the confidence intervals at a specific percentile overlap, there is no indication that the two distributions are significantly different at that percentile. Conversely, if the confidence intervals do not overlap at the selected percentile, then it is likely that the two distributions are significantly different at that percentile. It is, however, important to note that with small numbers of specimens the confidence intervals are, in general, relatively wide, so that the conclusions in such cases are rather weak.

This type of test is independent of the shape parameter of the two distributions. Note, however, that if the shape parameters are different, a significant difference may exist at one percentile, but not at another. The confidence intervals for the percentiles can be calculated as described in **4.5.1**.

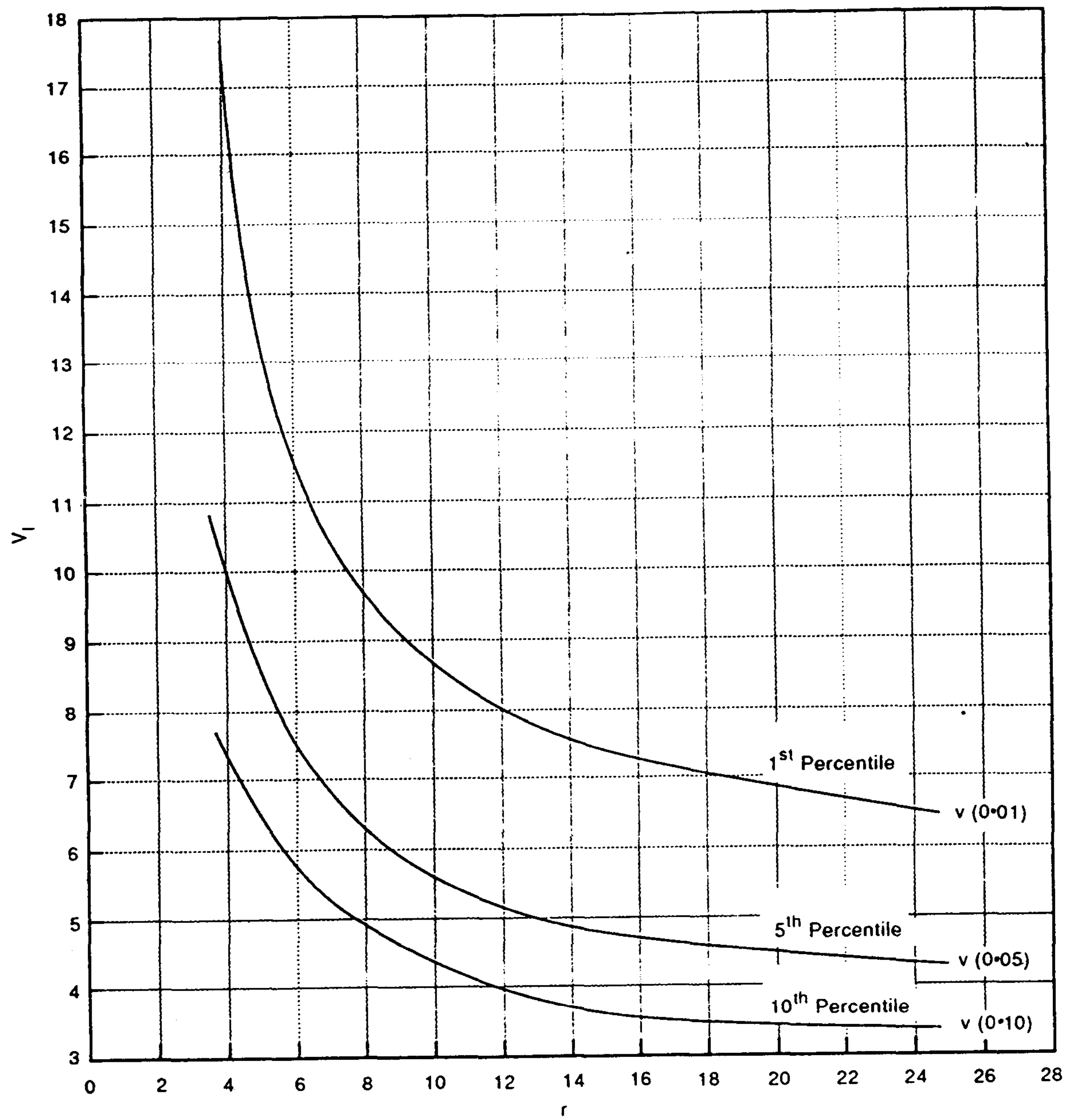

FIG. 7A V_1 FACTOR FOR CALCULATING THE 90 PERCENT TOLERANCE BOUNDS FOR GUMBEL AND WEIBULL (100 P TH) PERCENTILES

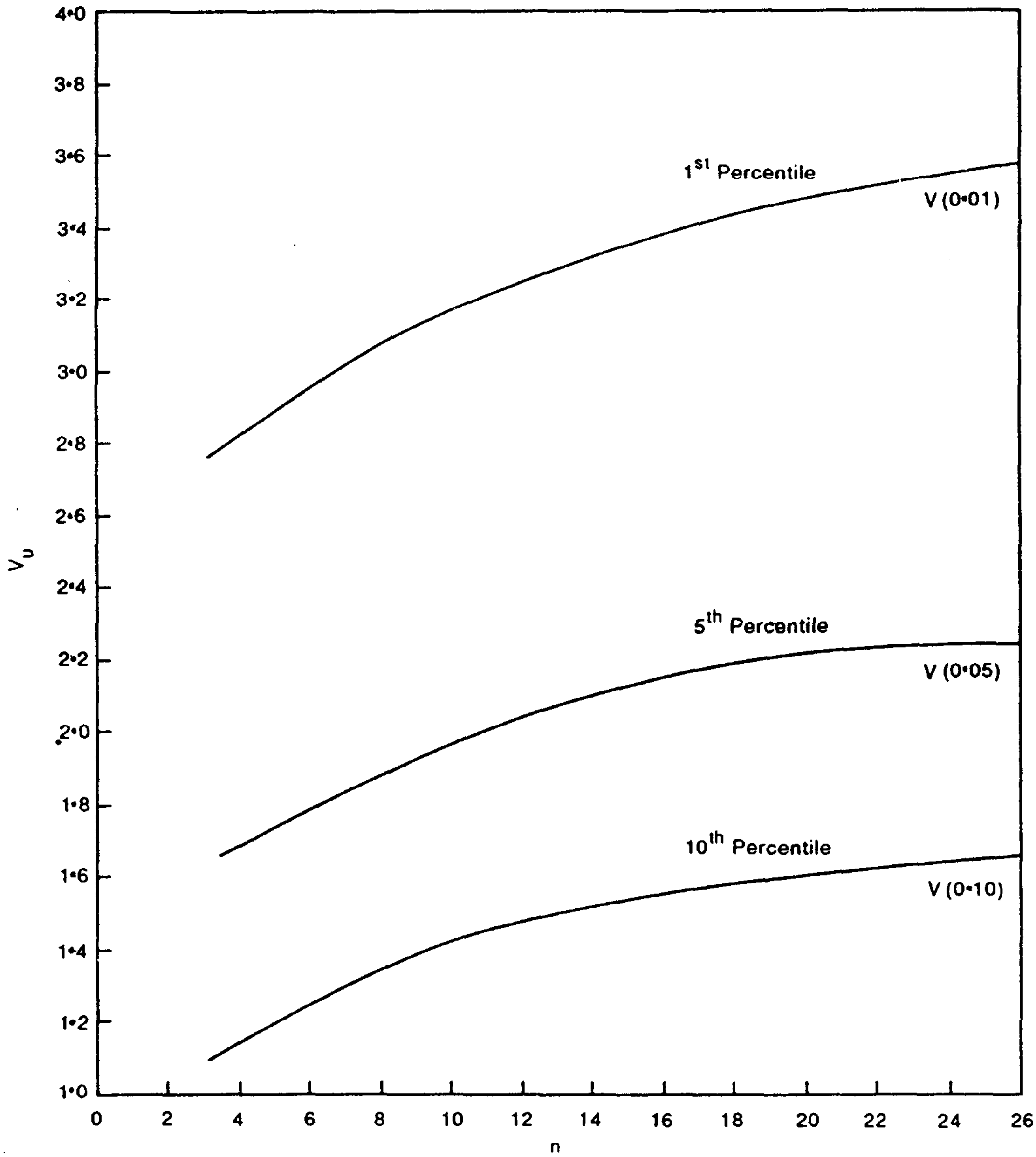

FIG. 7B V_u FACTOR FOR CALCULATING THE 90 PERCENT TOLERANCE BOUNDS FOR GUMBEL AND WEIBULL (100 P TH) PERCENTILES

It is often useful to analyze comparison test data on Weibull probability paper. Plot the data from the two (or more) tests on the same graph paper. As described in **4.5.1**, plot the 90 percent tolerance bounds for each data set. Where the confidence intervals do not overlap, there is a high probability that the two data sets are significantly different.

This procedure is illustrated with the test data in Table 3, which are also plotted in Fig. 8A. The 90 percent confidence interval for each data set is shown in Fig. 8B. For percentiles greater than about 10 percent, the two intervals do not overlap and therefore there is a significant difference between the two insulations at high field stresses and at high probabilities of failure. Note that for low probabilities of failure the intervals overlap and thus a significant difference is *not assured*. In principle, more specimens need to be tested to determine if a significant difference exists at low probabilities of failure.

Table 3 Breakdown Stresses (kV/mm) of Polyethylene from Two Manufacturing Processes

(*Clause* 5.2)

Failure No.	Process 1 (Screened)	Process 2 (Unscreened)
1	35	39
2	35	45
3	36	49
4	40	49
5	43	53
6	43	53
7	43	53
8	46	53
9	46	55
10	48	55
11	48	57
12	48	57
13	48	57
14	48	57
15	48	61
16	51	64
17	51	64
18	51	65
19	51	67
20	57	68

6 INTERPRETATION OF ELECTRICAL ENDURANCE DATA

The purpose of electrical endurance testing is to establish a relationship between the laboratory test life and the laboratory test voltage (or voltage stress) for the specific insulation system tested, over the range of test conditions employed in the test programme.

This laboratory performance relationship cannot be used direcly to establish intended performance of the insulation system under service conditions in absolute terms. As is recognized in IS 11182 (Part 1), it is desirable ultimately to be able to make evaluations, directly, in absolute terms. However, based on the present state of the art of electrical insulation technology, direct evaluation is not possible. Only comparative evaluations are possible at this time.

If the estimated performance under service conditions of the identical insulation system that was subjected to laboratory testing can be evaluated in accordance with the principles outlined in IS 11182 (Part 6) then a relationship between laboratory performance and estimated service performance can be established for this insulation system.

If, in turn, the laboratory performance of a second insulation system is established by using an identical laboratory test programme, then the intended performance of the second insulation system under service conditions can be established by comparison with the relationship between the laboratory and estimated service performance of the first insulation system.

The usefulness of these relationships is dependent on the validity and accuracy of the failure model chosen to represent them.

6.1 Choosing a Failure Model

The selection of the most valild failure model for the test programme is equivalent to establishing the relationship between failure time and test voltage over the range of voltages covered by the several different constant voltage tests in the test programme.

It is well known that, in general, elapsed test time in a voltage endurance test decreases as the test voltage stress increases. Although no individual model has been conclusively proven to be valid, two mathematical models have been most commonly selected to express this relationship quantitatively. Other models have also been used but will not be described here.

6.1.1 *Inverse Power Model*

The inverse power model is described by the equation:

$$L = kV^{-N} \qquad \text{.......(35)}$$

where L is the time-to-breakdown at constant voltage V, and k and N are constants. As the voltage increases, the time to breakdown decreases in inverse proportion to the voltage raised to the exponent N. A threshold value can also be incorporated.

If the co-ordinates of time to breakdown and voltage (or voltage stress) fit a straight line when plotted on log-log graph paper, then the inverse power model and the equation (35) can be assumed to be valid.

6.1.2 *Exponential Model*

The exponential model is described by an equation such as :

$$L = C \exp [-(V - V_t)], V > V_t \qquad \text{......(36)}$$

where C and V_t are constants. This model has a built-in threshold principle such that breakdown cannot occur at voltages (or voltage stresses) less than V_t.

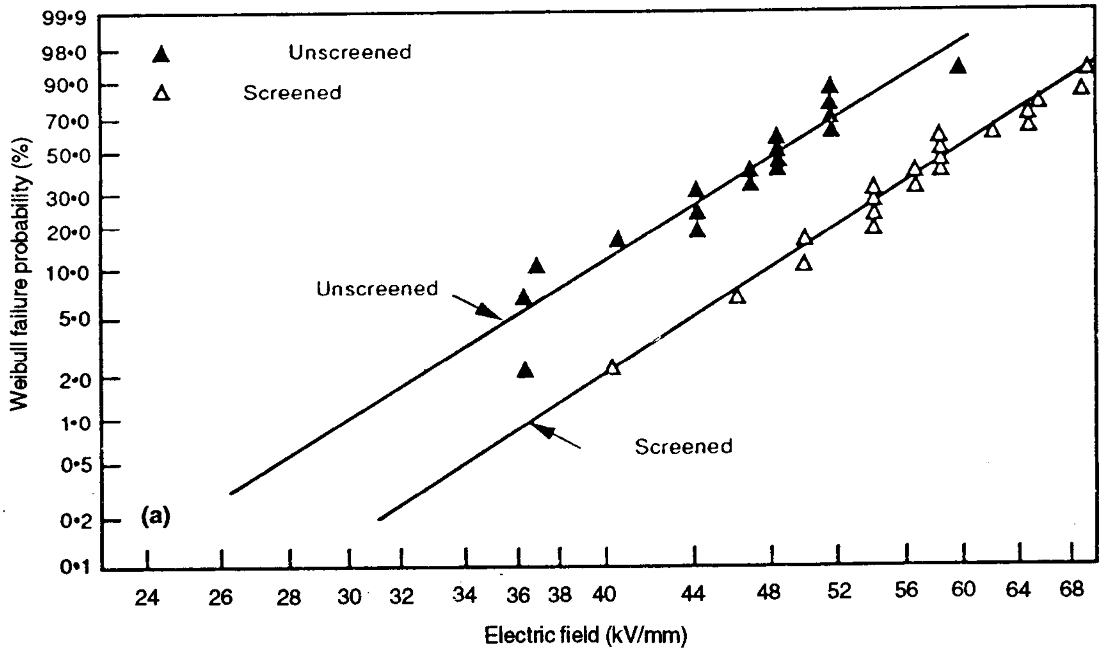

FIG. 8A

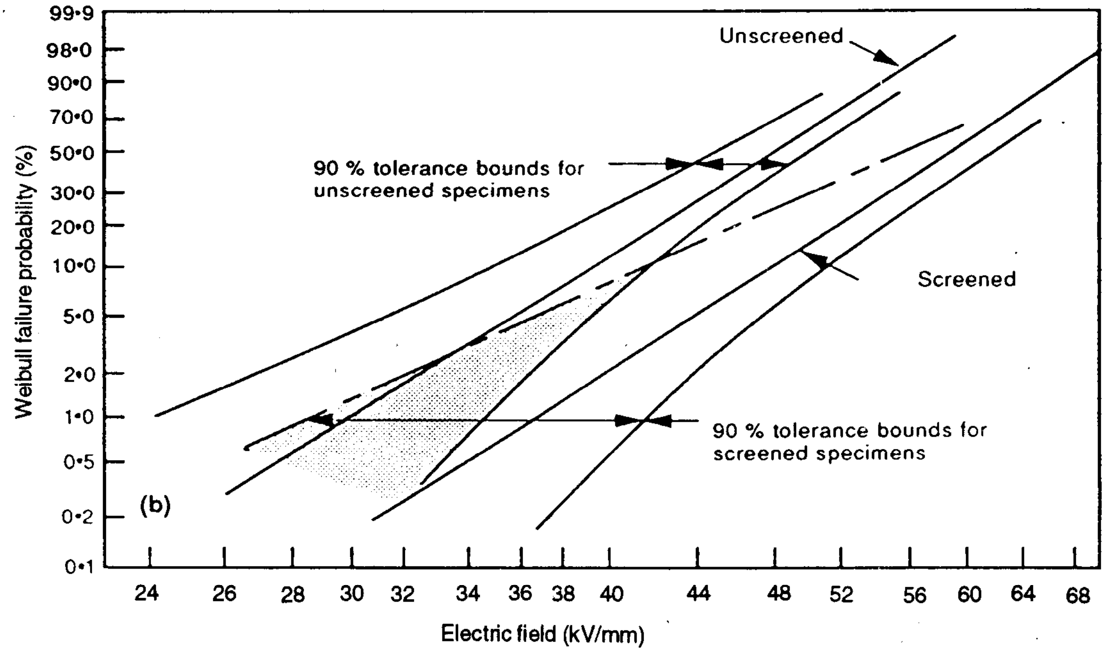

FIG. 8B

FIG. 8 COMPARISON OF DATA SETS

If the co-ordinates of time to breakdown and voltage (or voltage stress) do not fit a straight line when plotted on log-log paper, as described in **6.2**, but do fit a straight line when the time to breakdown is referred to a logarithmic scale and the voltage (or voltage stress) is referred to a linear scale, then the exponential model and the equation (36) can be assumed to be valid.

6.2 Handling the Test Data

The co-ordinates required for introduction into the selected failure model are time to breakdown and voltage (or voltage stress). The time to breakdown must be the characteristic or representative value derived from the calculations described in 4 for each level of voltage employed in the test programme. It is beneficial to have the confidence intervals at the characteristic values for inclusion as well.

6.2.1 *Progressive Voltage Stress Tests*

The test data resulting directly from the progressive voltage stress tests will be in the form of test voltage and rate of rise of voltage.

For introduction into the selected failure model, these data must be transformed into coordinates of time to breakdown and voltage (or voltage stress). A number of procedures for making this mathematical transformation have appeared in the technical literature, and will not be described here.

6.2.2 *Constant Voltage Stress Tests*

The test data resulting from constant stress will be in a suitable form for direct introduction in the selected failure model.

6.3 Plotting the Data

The co-ordinates derived in **6.2** are plotted in accordance with the selected failure model.

Since the data provided by extreme value distributions at each test voltage are not symmetrical, it is not strictly valid to use a linear regression method to establish the equation for the straight line which best fits the relationship between those data on the voltage (or voltage stress) versus time graph.

An approximate procedure is to make a linear regression analysis of the logarithms of the time to breakdown data using any conventional arithmetic procedure or computer programme, and plot the antilogarithms of resulting line coordinates on the appropriate graph for the selected failure model. Confidence intervals at varying voltages (or voltage stresses) can also be calculated and plotted.

An example of the handling of a set of hypothetical data is given in Annex B. For this example, the inverse power model has been assumed and calculated confidence intervals have been included. The voltage endurance data have been plotted on a log-linear graph in Fig. B3 and on a log-log graph in Fig. B4.

6.4 Interpretation

The plot of time-to-breakdown against voltage (or voltage stress) and the exponent of the derived equation, as described in **6.3**, become the figures of merit for the electrical endurance of the specific insulation system under the conditions of the test.

6.5 Limitations

Any conclusions derived from statistical analysis of test data are rigorously valild only within the limits of the test conditions used to derive the data, and for the specific insulation systems included in the test programme.

Extrapolation beyond the limits of the conditions of test is dangerous, and if a discontinuity exists in the relationship between failure rate and time, at different voltage stresses, extrapolation beyond that discontinuity is completely invalid and erroneous. In the absence of such discontinuity, the error of prediction (even with a correct model) becomes excessively large very quickly.

7 TEST PROCEDURES AND REPORTS

When insulation systems are tested, it is important for uniformity that the test procedures specify the following:

a) the extrapolation model that should be used;

b) whether voltage or voltage stress should be used;

c) whether voltage should be expressed in r.m.s or peak values;

d) the voltage range or voltage stress range over which the endurance values of insulation systems may be extrapolated, or the value to which the extrapolation should be limited;

e) the statistical treatment that should be used; and

f) the specific values that should be used to quantify performance.

The report should include the plot of time to breakdown versus voltage (or voltage stress) and the numerical value of the exponent of the mathematical relationship, as well as the details specified by the equipment technical committee.

These conditions and cosiderations may be different for various types of equipment and insulation systems.

ANNEX A

(*Clause* 4.3.2.1)

(Informative)

BASIC PROGRAMME TO CALCULATE $\hat{\alpha}$ et $\hat{\beta}$

```
10   REM PROGRAMME CALCULATES MAXIMUM LIKELIHOOD ESTIMATES
12   REM OF WEIBULL PARAMETERS
15   REM A FIRST GUESS FOR BETA IS REQUIRED
20   DIM TIME (25), LNTIME (25), A (3)
30   PRINT 'INPUT N-NO. OF SAMPLES TESTED'
40   INPUT N
50   PRINT 'INPUT R-NO. OF SAMPLES FAILED'
60   INPUT R
70   PRINT 'INPUT TS-TIME OR VOLTAGE TEST STOPPED'
80   INPUT  TS
85   LTS = LOG (TS)
90   PRINT 'INPUT FIRST ESTIMATE FOR BETA'
100  INPUT BETA
110  ITER = 0
120  C = 0
130  PRINT 'INPUT THE FAILURE TIMES OR VOLTAGES'
140  FOR I = 1 TO R
150  INPUT TIME (I)
160  LNTIME (I) = LOG (TIME (I))
170  C = C + LNTIME (I)
180  NEXT I
190  C = C/R
200  FOR J = 1 TO 3
210  SUM = 0
220  FOR K = 1 TO R
230  SUM = SUM + ((TIME (K)^BETA)*(LNTIME(K)^(J-1)))
240  NEXT K
250  A(J) = SUM + (N-R)*(TS^BETA)*(LTS^(J-1))
260  NEXT J
270  QUOT = A (2) / A(1)
280  FPRIME = A(3) / A(1) - (QUOT^2) + ((1./BETA)^2)
290  F = QUOT - (1./BETA) - C
300  BETA =BETA - F/FPRIME
310  ITER = ITER +1
320  IF ITER>20 THEN 370
330  IF ABS (F)>0.0001 THEN 200
340  ALPHA = (A(1)/R)^(1./BETA)
350  PRINT 'ALPHA ='; ALPHA
352  PRINT 'BETA ='; BETA
354  PRINT 'ITERATIONS ='; ITER
360  STOP
370  PRINT 'DID NOT CONVERGE'
380  PRINT 'NEED A BETTER ESTIMATE OF BETA'
390  STOP
400  END
READY
```

ANNEX B

(*Clause* 6.3)

(Informative)

MAXIMUM LIKELIHOOD FIT OF A WEIBULL DISTRIBUTION TO MULTIPLE CENSORED DATA

Insulation system XYZ 8 kV/mm (r.m.s value)
Test data

Number of specimens tested = 10
Number of specimens failed = 10

Failure time

8 800
14 000
26 000
29 000
36 000
48 000
56 000
78 000
88 000
94 000

Survival time

Converged after 5 iterations

Output
Alpha = 53 582.97
Beta = 1.689 049

Insulation system XYZ 10 kV/mm (r.m.s. value)

Test data

Number of specimens tested = 10
Number of specimens failed = 10

Failure time

150
280
490
800
1 000
1 250
1 500
1 600
2 100
3 000

Survival time

Converged after 5 iterations

Output
Alpha = 1 340.608
Beta = 1.446 667

Insulation system XYZ 12 kV/mm (r.m.s value)

Test data

Number of specimens tested = 10
Number of specimens failed = 10

Failure time

80
120
180
300
320
360
430
600
750
800

Survival time

Converged after 5 iterations

Output
Alpha = 442.501 8
Beta = 1.701 543

Insulation system XYZ 14 kV/mm (r.m.s value)

Test data

Number of specimen tested = 10
Number of specimen failed = 10

Failure time

4
6
7
12
17
19
24
29
33
40

Survival time

Converged after 5 iterations

Output
Alpha = 21.422 23
Beta = 1.680 513

Insulation System XYZ 8 kV/mm (r.m.s. Value)

(*Co-ordinates for Figure* B1)

Sample No.	Insulation System	Status	VE hours	Rank i	k $n-(i-1)$	Hazard 100/k	Accumulated Hazard SUM (100 /K)
1	XYZ	Failed	8 800	1	10	10.0	10.0
2	XYZ	Failed	14 000	2	9	11.1	21.1
3	XYZ	Failed	26 000	3	8	12.5	33.6
4	XYZ	Failed	29 000	4	7	14.3	47.9
5	XYZ	Failed	36 000	5	6	16.7	64.6
6	XYZ	Failed	48 000	6	5	20.0	84.6
7	XYZ	Failed	56 000	7	4	25.0	109.6
8	XYZ	Failed	78 000	8	3	33.3	142.9
9	XYZ	Failed	88 000	9	2	50.0	192.9
10	XYZ	Failed	94 000	10	1	100.0	292.9

Insulation System XYZ 10kV/mm (r.m.s. Value)

(*Co-ordinates for Figure* B1)

Sample No.	Insulation System	Status	VE hours	Rank i	k $n-(i-1)$	Hazard 100/k	Accumulated Hazard SUM (100 /K)
1	XYZ	Failed	150	1	10	10.0	10.0
2	XYZ	Failed	280	2	9	11.1	21.1
3	XYZ	Failed	490	3	8	12.5	33.6
4	XYZ	Failed	800	4	7	14.3	47.9
5	XYZ	Failed	1 000	5	6	16.7	64.6
6	XYZ	Failed	1 250	6	5	20.0	84.6
7	XYZ	Failed	1 500	7	4	25.0	109.6
8	XYZ	Failed	1 600	8	3	33.3	142.9
9	XYZ	Failed	2 100	9	2	50.0	192.9
10	XYZ	Failed	3 000	10	1	100.0	292.9

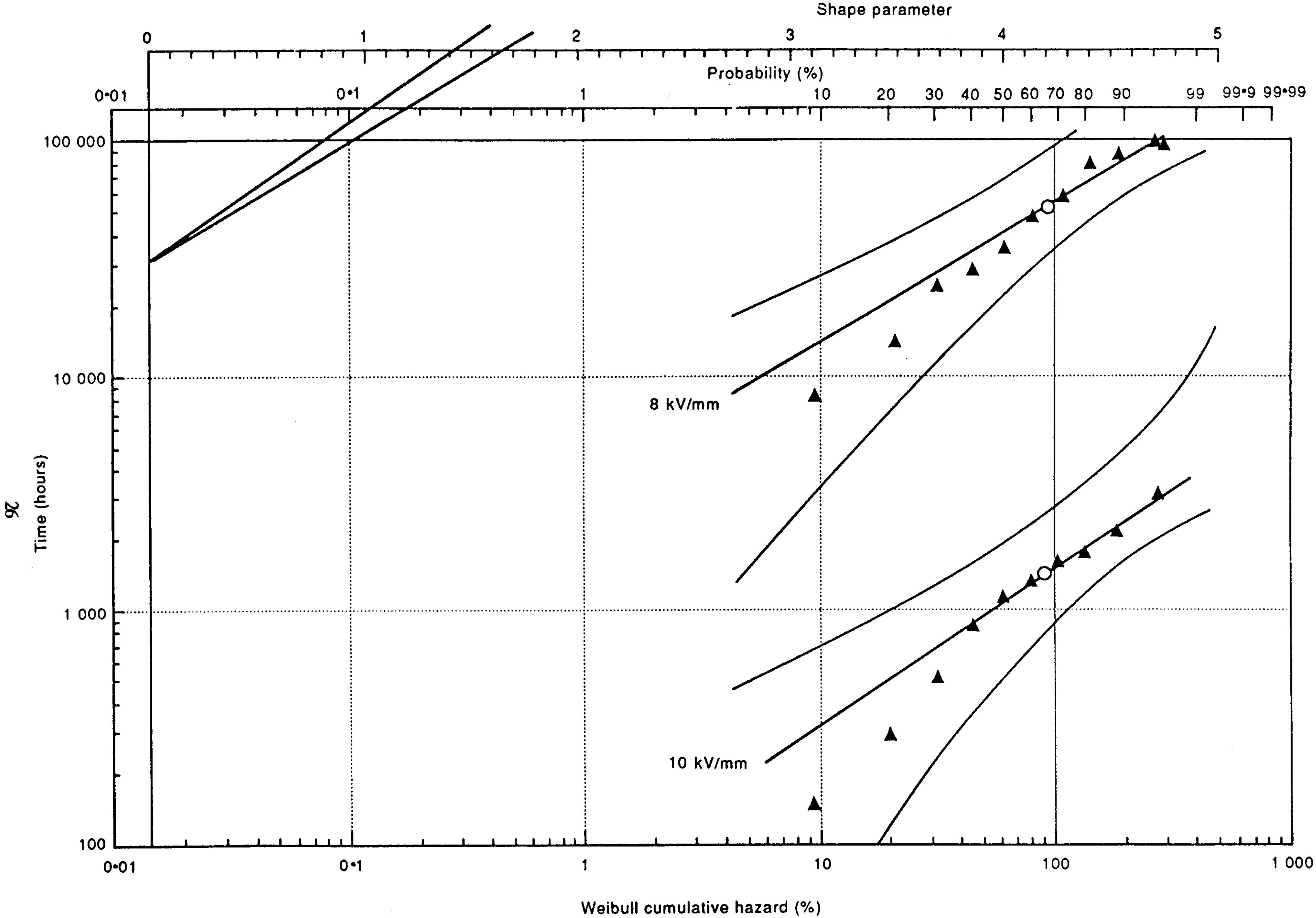

FIG. B1 VOLTAGE ENDURANCAE – SYSTEM XYZ

Insulation System XYZ 12 kV/mm (r.m.s. Value)

(*Co-ordinates for Figure* B2)

Sample No.	Insulation System	Status	VE hours	Rank i	k $n-(i-1)$	Hazard 100/k	Accumulated Hazard SUM (100 /K)
1	XYZ	Failed	80	1	10	10.0	10.0
2	XYZ	Failed	120	2	9	11.1	21.1
3	XYZ	Failed	180	3	8	12.5	33.6
4	XYZ	Failed	300	4	7	14.3	47.9
5	XYZ	Failed	320	5	6	16.7	64.6
6	XYZ	Failed	360	6	5	20.0	84.6
7	XYZ	Failed	430	7	4	25.0	109.6
8	XYZ	Failed	600	8	3	33.3	142.9
9	XYZ	Failed	750	9	2	50.0	192.9
10	XYZ	Failed	800	10	1	100.0	292.9

Insulation System XYZ 14 kV/mm (r.m.s. Value)

(*Co-ordinates for Figure* B2)

Sample No.	Insulation System	Status	VE hours	Rank i	k $n-(i-1)$	Hazard 100/k	Accumulated Hazard SUM (100 /K)
1	XYZ	Failed	4	1	10	10.0	10.0
2	XYZ	Failed	6	2	9	11.1	21.1
3	XYZ	Failed	7	3	8	12.5	33.6
4	XYZ	Failed	12	4	7	14.3	47.9
5	XYZ	Failed	17	5	6	16.7	64.6
6	XYZ	Failed	19	6	5	20.0	84.6
7	XYZ	Failed	24	7	4	25.0	109.6
8	XYZ	Failed	29	8	3	33.3	142.9
9	XYZ	Failed	33	9	2	50.0	192.9
10	XYZ	Failed	40	10	1	100.0	292.9

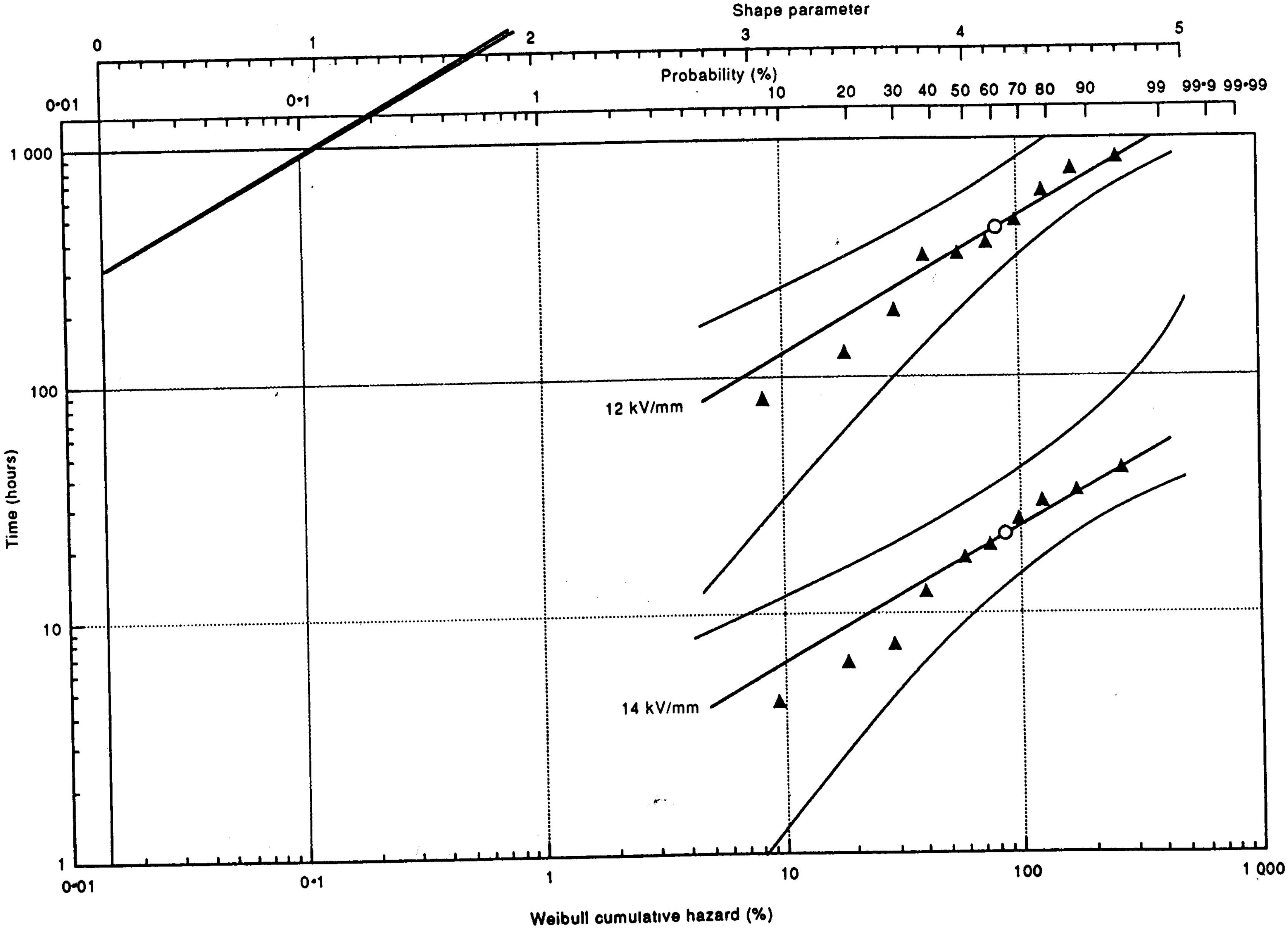

FIG. B2 VOLTAGE ENDURANCAE – SYSTEM XYZ

Linear Regression of Logarithm of Time on Logarithm of Voltage Stress, $y = a + b \times$ Insulation System : XYZ

(*Co-ordinates for Figure* B2)

Voltage Stress U kV/mm	lg U(kV/mm) x	Time (t) hours	lg t (s) y	xy	x^2	y^2
14	1.15	21	4.88	5.59	1.31	23.80
12	1.08	443	6.20	6.69	1.16	38.47
10	1.00	1 341	6.68	6.68	1.00	44.67
8	0.90	53 583	8.29	7.48	0.82	68.65
Σ	4.13		26.05	26.45	4.29	175.59

Number of observations: $n = 4$ Degrees of freedom: $f = n - 2 = 2$

Average values: $\bar{x} = \dfrac{\sum x}{n} = 1.03$ $\bar{y} = \dfrac{\Sigma y}{n} = 6.51$

Regression coefficients $a = \bar{y} - b\bar{x} = 20.17$ $b = \dfrac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2} = -13.23$

Dispersion of deviations of y from regression line $s = \sqrt{\dfrac{\left(\sum y^2 - n\bar{y}^2\right) - b\left(\sum xy - n\bar{x}\bar{y}\right)}{f}} = 0.30$

Standard error of a $s_a = \dfrac{s}{\sqrt{n}} = 0.15$

Standard error of b $s_b = \dfrac{s}{\sqrt{\Sigma x^2 - nx^2}} = 1.66$

For x =	0.00	2.00	4.00	6.00	8.00	10.00
y =	1.52	1.37	1.22	1.07	0.92	0.77
U kV/mm =	33.5	23.6	16.7	11.8	8.3	5.9

Correlation coefficient $r = \dfrac{\sum xy - n\bar{x}\bar{y}}{\sqrt{\left(\sum x^2 - nx^2\right)\left(\sum y^2 - ny^2\right)}} = -0.98$

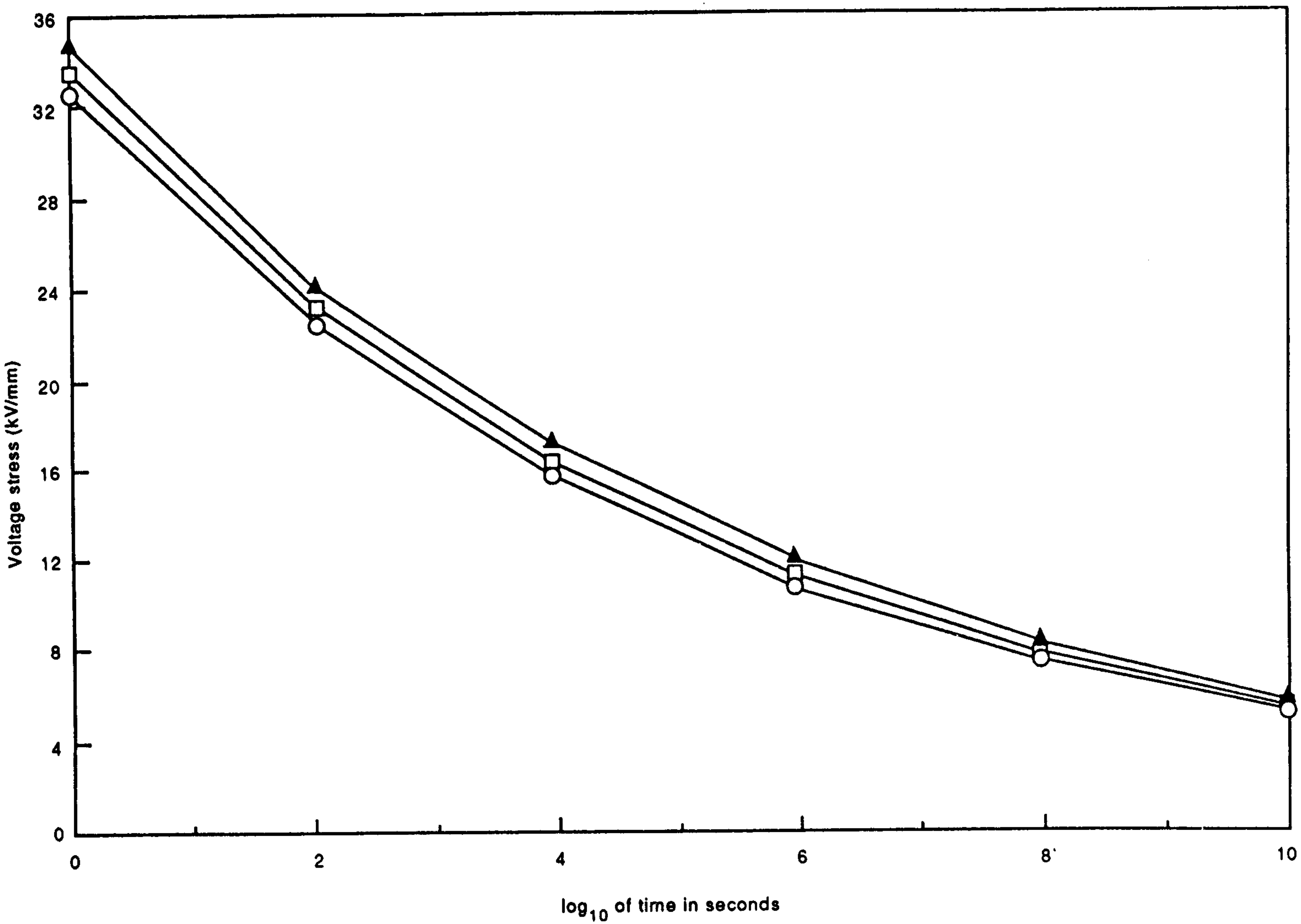

FIG. B3 VOLTAGE ENDURANCAE – SYSTEM XYZ (95 PERCENT CONFIDENCE INTERVAL)

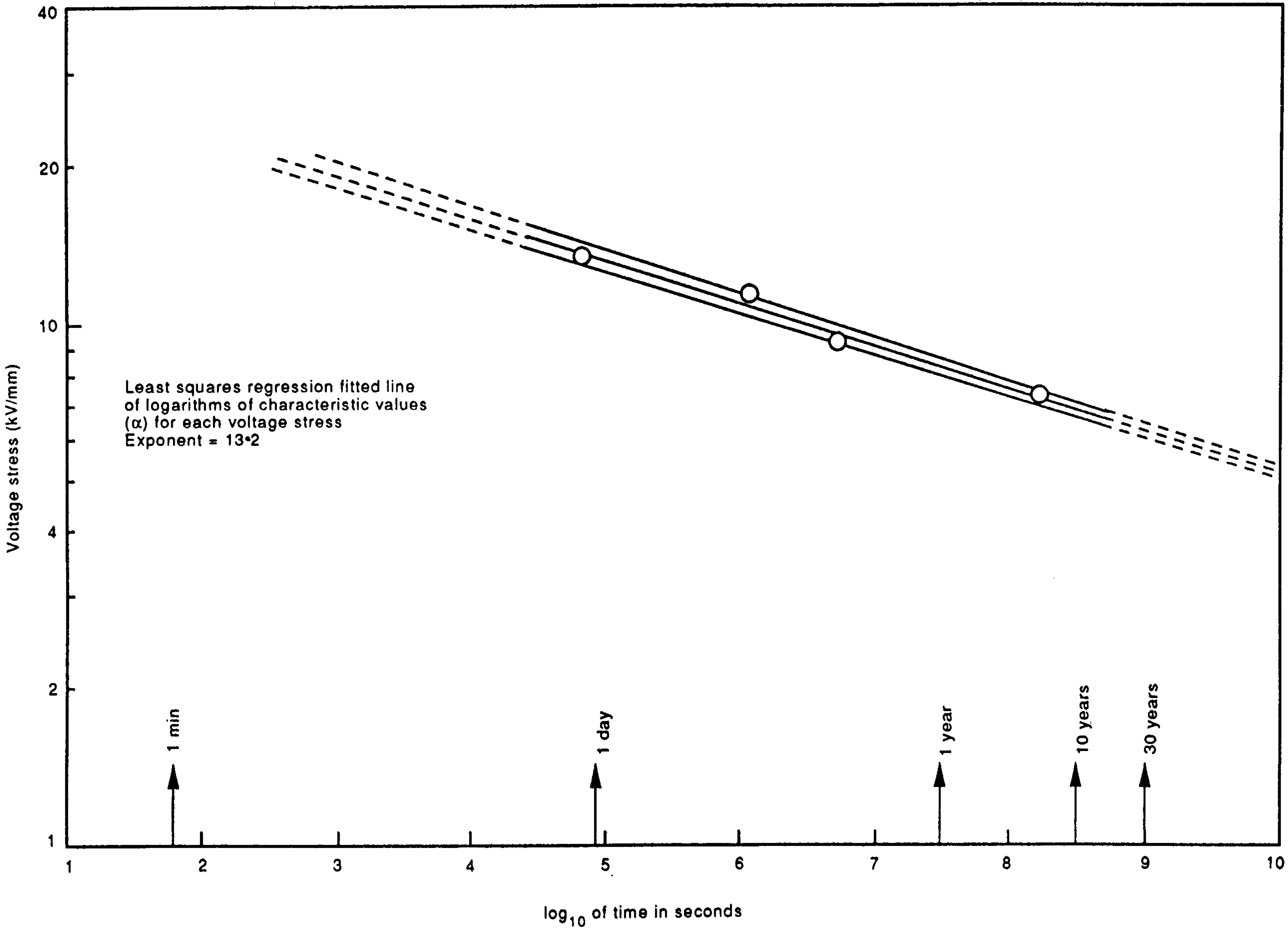

FIG. B4 VOLTAGE ENDURANCAE – SYSTEM XYZ

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Amendments Issued Since Publication

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